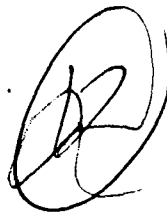


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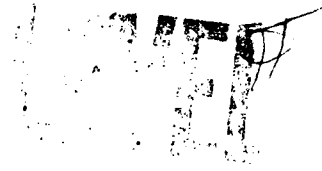
ARI TECHNICAL REPORT
TR-78-TH7

Prediction of the Recognition of Real Objects as a Function of Photometric and Geometric Characteristics

by

Deborah G. Bonnet and Harry L. Snyder

VIRGINIA POLYTECHNIC INSTITUTE AND
STATE UNIVERSITY
Blacksburg, Virginia 24061



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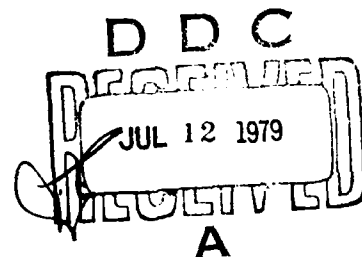
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Item 20 (continued)

Seventeen characteristics of targets, backgrounds, and target/background relationships which reliably correlate to target acquisition performance were identified. Sixty regression equations combining these variables into linear predictive models of target acquisition performance were developed from one set of targets and mission conditions and cross-validated against targets contained in three different reconnaissance missions.

The best prediction is obtained when at least two orthogonal scans are passed through the target of at least two frames of the reconnaissance film. With three properly weighted predictor variables derived from these scans, up to 92% of the variance in target detectability is predicted. The prediction equation contains one measure of target size, one of background heterogeneity, and one of target/background contrast. Performance is most predictable when the minimum available range is taken as the criterion in the event of an incorrect response.

The report is of primary interest to research personnel.

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PREDICTION OF THE RECOGNITION OF REAL OBJECTS AS A FUNCTION
OF PHOTOMETRIC AND GEOMETRIC CHARACTERISTICS

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SUMMARY

The need exists for an objective, field-amenable technique of predicting air-to-ground tactical target-by-target acquisition performance. Some existing data require psychophysical inputs from many subjects, which is impractical in field situations. Because small computers and automatic microdensitometric scanners are now available and field-transportable, automatic mission success prediction is feasible if:

1. Aerial photographic reconnaissance imagery is available and specific targets of interest have been acquired on that imagery;
2. One knows what type of and how many scans to make from the imagery;
3. One knows what measures to extract from the scans; and
4. One knows how to combine these measures into an equation to predict mission success.

The primary objective of this research was to obtain data which can be used to define optimal conditions for the last three requirements listed above.

Microdensitometric scans were made from air-to-ground reconnaissance films containing 12 tactical targets. Data obtained from these microdensitometric scans were used to derive a total of 36 photometric and geometric predictor variables, which were employed in a stepwise linear multiple regression analysis to predict air-to-ground target acquisition performance. The 36 predictors were reduced to 17 by a consistency criterion, with the resulting 17 variables used to generate a linear model which predicted range to target at the time of acquisition. This prediction model was evaluated for accuracy with both one and two different images of the same target, and for single and multiple microdensitometric scans through the target in each image.

It appears feasible to predict the ground range at which a given target will be detected by an airborne observer. This prediction may be made totally automatically, given reconnaissance imagery, a microdensitometer, and a small computer.

The best prediction is obtained when at least two orthogonal scans are passed through the target of at least two frames of the reconnaissance film. With three properly weighted predictor variables derived from these scans, up to 92% of the variance in target acquisition range is predicted. The prediction equation contains one measure of target size, one of background heterogeneity, and one of target/background contrast. Performance is most predictable when the minimum available range is taken as the criterion in the event of an incorrect response.

These results indicate the feasibility and accuracy of prediction of in-flight air-to-ground target acquisition performance from reconnaissance imagery physical measures. With further examination of the generalizability of these results to various mission types, implementation of these results into appropriate hardware would appear appropriate.

INTRODUCTION

The ability of airborne observers to detect, recognize, and identify a specific object in a typical contextual background is essential to the success of numerous military operations. Aircrews must visually locate navigational checkpoints, terminal areas for landing and cargo drops, and targets of military significance.

The advent of remote-sensing imaging systems designed to facilitate the visual identification of critical objects has instigated much research comparing the advantages of one imaging system to another. The general intent of these studies has been to identify the parameters of a visual display which optimize image quality and thus object recognition (or target acquisition) performance. The average performance of many subjects in detecting many targets, perhaps under many mission conditions, has been studied as a function of various parameters of the imaging system. Such research (e.g., Snyder, 1973) provides behavioral evidence indicating in which of several systems long-term investments will be most effective, as well as an estimate of overall system-average object recognition performance. This information is certainly useful, but it is not sufficient.

The field commander is frequently in the position of deciding whether the possible benefits of sending an attack aircraft on a specific mission outweighs the probable risks. Knowing that with his visual display system (which may be nothing other than a window), the probability of successfully detecting an "average" target under "average" viewing conditions is, say, 75%, is of little use to him. What he needs to know is: Given this system and these viewing conditions, what is the probability that this mission will be successful? The field commander, then, needs specific information about the detectability of specific tactical targets, whether such targets are unexpected, targets of opportunity, or perhaps had been previously acquired on reconnaissance imagery. Unfortunately, useful data of this sort are seriously lacking, although a few previous studies bear some relationship to these questions.

Previous Research

An effort to apply the basic literature on form perception (see Zusne, 1970) to real objects in real backgrounds typically leads to futility, for most of the experiments, models, and analyses have been limited to abstract geometric shapes as target objects, usually contained in an unstructured background of other geometric shapes.

One can, however, turn to a narrow segment of the literature dealing with air-to-ground and ground-to-ground target acquisition, in which quantifiable target, background, and target/background characteristics affecting target acquisition performance have been investigated. In this literature, three methods of measuring scene characteristics have

emerged: psychophysical judgment, geometric measurement, and photometric scanning.

Nygaard, Slocum, Thomas, Skeen, and Woodhull (1964) used a flying-spot scanner and video analyzer to quantify five dimensions of scene complexity: the (1) mean and (2) variance of the size of all contrasting objects in the scene; the (3) mean and (4) variance of the scene's brightness; and (5) the total number of contrasting elements per unit area. These complexity characteristics were related to the performance of trained photointerpreters in static target acquisition, where performance was measured in logarithmic units of search time. Radar, infrared, and photographic reconnaissance imagery were included.

Log search time increased with mean object size, mean object size variance, and total object count for infrared and photographic imagery. The mean and variance of the scene's brightness were not related to performance with infrared or photographic imagery, and attempts to relate scene complexity to target acquisition in radar imagery were unsuccessful.

Corbett, Diamantides, and Kaue (1964) also employed a flying-spot scanner to quantify physical characteristics of radar imagery which may relate to static target acquisition. Instead of dealing with the scene as a whole, their predictors reflected the relationship between a target and its immediate background. Four predictors of target acquisition performance were the target-to-background ratios of mean transmissivity,¹ transmissivity variance, the mean derivative of the transmission function, and the variance of the derivatives. Target size was the fifth predictor. The criterion of target acquisition was reciprocal search time (or search speed).

Corbett et al. (1964) developed several linear and nonlinear multiple regression equations to relate the four photometric predictors to target acquisition of radar imagery. When target size was used, it was a multiplier, not an additive component. The logarithmic model fit best; with an N of 20 targets, the multiple correlation (R) was .69. The results of cross-validating the model against a different set of 17 targets were not as encouraging; R shrank to .28. When the logarithmic model was validated against 15 optical and 13 infrared targets, Rs were .07 and .04, respectively.

Rhodes' (1964) attempt at target-by-target prediction was considerably more successful, but relied primarily on psychophysically determined predictor variables instead of objective measures of target and background characteristics. Judges made relative ratings of 100 aerial reconnaissance photographs on 12 dimensions. These 12 psychophysical

¹Transmissivity of the film is directly proportional to luminance in the projected display.

predictors plus 2 geometric ones (target size and distance from center) were related to judged target difficulty and to log search time. Multiple linear regression analyses were performed to relate the 14 predictors to log search time. R ranged from .75 to .90. The regression equations were cross-validated against 100 different photographs viewed by different subjects, resulting in an average validity coefficient of .81 with the highest .84. A factor analysis isolated seven factors related to target acquisition performance; the most important factors were target size, target shape-pattern, and target isolation.

A simple correlation was computed between judged target difficulty and log search time; R was .73. "Thus, the single complex judgment made by raters in answering the question, 'How hard would it be to find this particular target in this photograph?' contains almost as much predictive information as several separate judgments about presumably relevant image characteristics" (Rhodes, 1964, p. 24). While this result is of interest and certainly indicates the multidimensional complexity of the problem, its use in a field environment is awkward at best, and probably of little use due to inherent biases on the part of field available personnel.

The literature contains only one study relating target and background parameters to dynamic (relative motion between scene and observer) target acquisition (Zaitzeff, 1971). The cumulative target acquisition probability as a function of ground range was obtained for 10 targets on a color motion picture reconnaissance film. The field of view was divided into equal areas representing 10 ground distances; the probability of recognition of a target before it left a given area served as the criterion, giving an N of 100 (10 targets \times 10 distances).

Fourteen target and background characteristics were investigated as predictors of target acquisition. Two were psychophysically determined, six were directly measured geometric parameters of the target, and eight were calculated from a single microdensitometric scan through the target. The seven best predictors were target length and width (geometric), detail contrast, target contrast, element count (photometric scan analysis), ambiguity, and heterogeneity (psychophysical). Combined in a linear regression equation, these seven variables predicted 79% of the criterion variance ($R = .89$). The prediction equation was not cross-validated. An R of .89 was also obtained when static target acquisition was correlated with dynamic target acquisition performance.

A study conducted by Snyder, Keese, Beamon, and Aschenbach (1974) suggested that photometric predictors should be viewed with more optimism. A single microdensitometric scan was passed through the center of each of 21 targets appearing on a black-and-white reconnaissance motion picture film. Film transmission was recorded on an X-Y plotter and 32 predictor variables were generated through hand analysis of the transmission functions. Four dynamic performance measures were related to the 32 predictors in separate multiple linear stepwise regression

analyses. In each case, a single predictor accounted for at least 25% of the criterion variance; with 19 predictors in the equation, R was 1.00. However, there was little consistency across the four analyses in the order in which predictors entered into solution. Since results were not cross-validated, no conclusive statements could be made about the true predictive value of the scene characteristics under investigation, although the results appeared promising.

Objectives of this Research

The need clearly exists for an objective, field-amenable technique of predicting air-to-ground tactical target-by-target acquisition performance. Some existing data require psychophysical inputs from many subjects, which is impractical in field situations. Because small computers and automatic microdensitometric scanners are now available and field-transportable, automatic mission success prediction is feasible if:

1. Aerial photographic reconnaissance imagery is available and specific targets of interest have been acquired on that imagery;
2. One knows what type of and how many scans to make from the imagery;
3. One knows what measures to extract from the scans; and
4. One knows how to combine these measures into an equation to predict mission success.

The primary objective of this research was to obtain data which can be used to define optimal conditions for the last three requirements listed above.

METHOD

Overview

Thirty-six characteristics of targets, backgrounds, and their interrelationships were investigated as predictors of dynamic target acquisition. All were automatically calculated from magnetic tape records of microdensitometric scans taken from film frames containing the target. If these predictors can be combined into valid prediction equations, mission success can be objectively and automatically predicted in the field for targets previously acquired on reconnaissance imagery.

The results of Corbett et al. (1964) made it clear that cross-validation of predictive models must not be overlooked. Thus, in the present study, a number of prediction equations were developed and cross-validated on a different set of targets viewed under different mission conditions.

Unlike any previous research of this type, this research addresses the following questions. How many predictor variables should be included in a prediction model? How much microdensitometric information is needed? What criterion of dynamic acquisition performance is most predictable?

Because of the complex, iterative nature of this study, Figure 1 indicates the research objectives, which are concisely stated in conjunction with brief descriptions of the experimental methods and data analyses serving each objective. Frequent reference to this flow chart will aid the reader's understanding of the procedures and analyses which follow. The methodology is very briefly described below.

Two previous simulation experiments in this laboratory had provided performance data on target acquisition under different flight conditions ("missions"). The performance data obtained from these experiments served as the criteria to be predicted in this study. Films used in these previous simulation studies were scanned with a microdensitometer to produce photometric and geometric data from which the criteria scores would be predicted. The microdensitometric (photometric and geometric) data were used to derive a total of 36 predictor variables, which were evaluated in a stepwise multiple regression equation as predictors of the criteria scores. From regression analyses, the most reliable predictors were selected and used in a linear stepwise multiple regression equation to obtain a "model" of criteria prediction for one of the missions. This model was then applied to two other missions to cross-validate the model. Analysis of variance techniques were then used to assess the quality of the model.

Reconnaissance Imagery Used in Previously Completed Experiments

The criterion (target acquisition performance) data, which will be predicted by the analyses of the present research, were previously obtained in a series of experiments in the Virginia Polytechnic Institute and State University (VPI&SU) Human Factors Laboratory. Because of the central importance of these criterion data, they shall be described first.

Three black-and-white 35 mm motion picture films were selected from the film library developed by the Autonetics Division of North American Rockwell (Humes and Bauerschmidt, 1968). Filmed over a 3000:1 scale terrain model, each represents a reconnaissance mission under different simulated flight conditions.

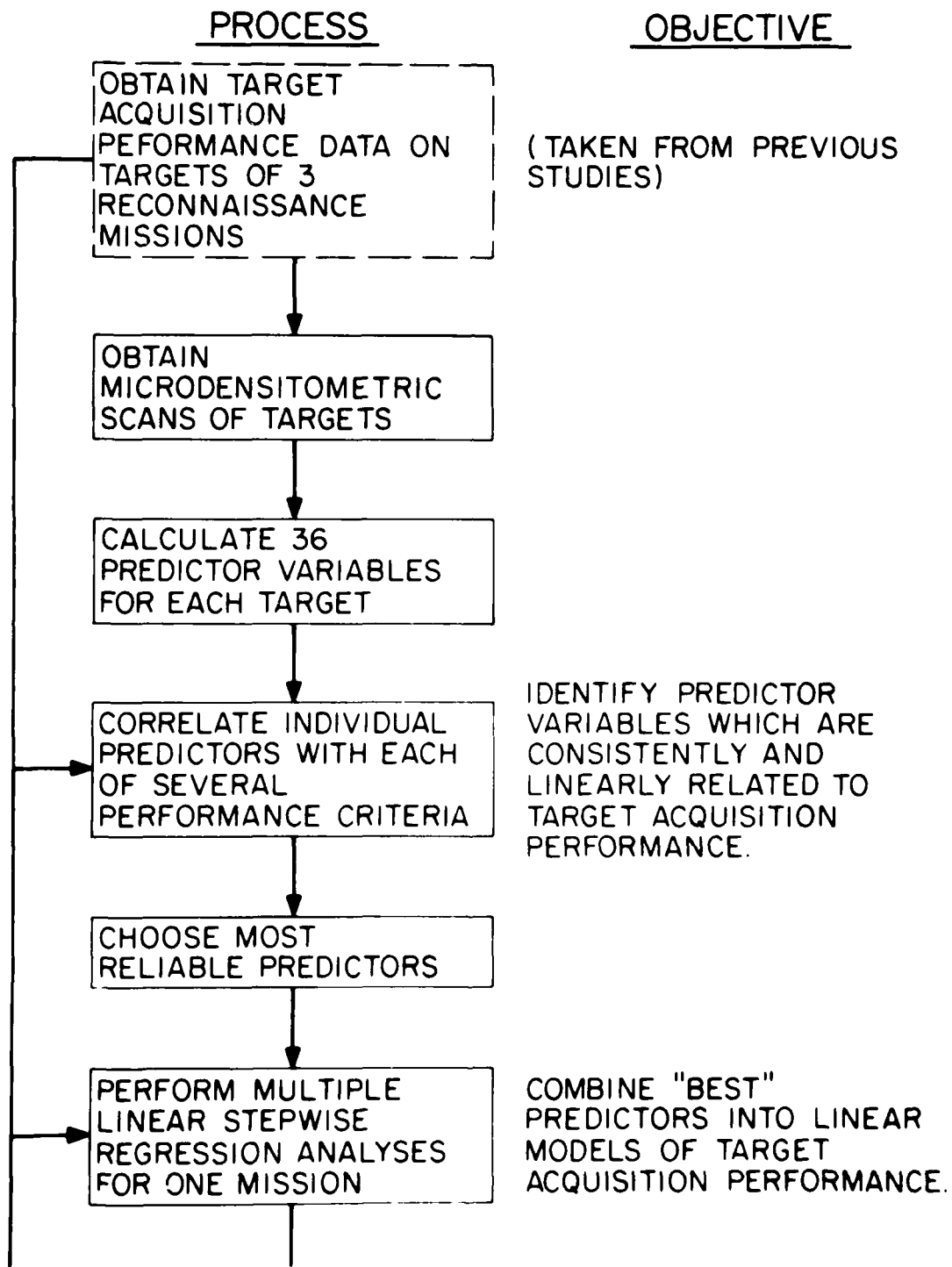


Figure 1. Flow chart of experimental procedures.

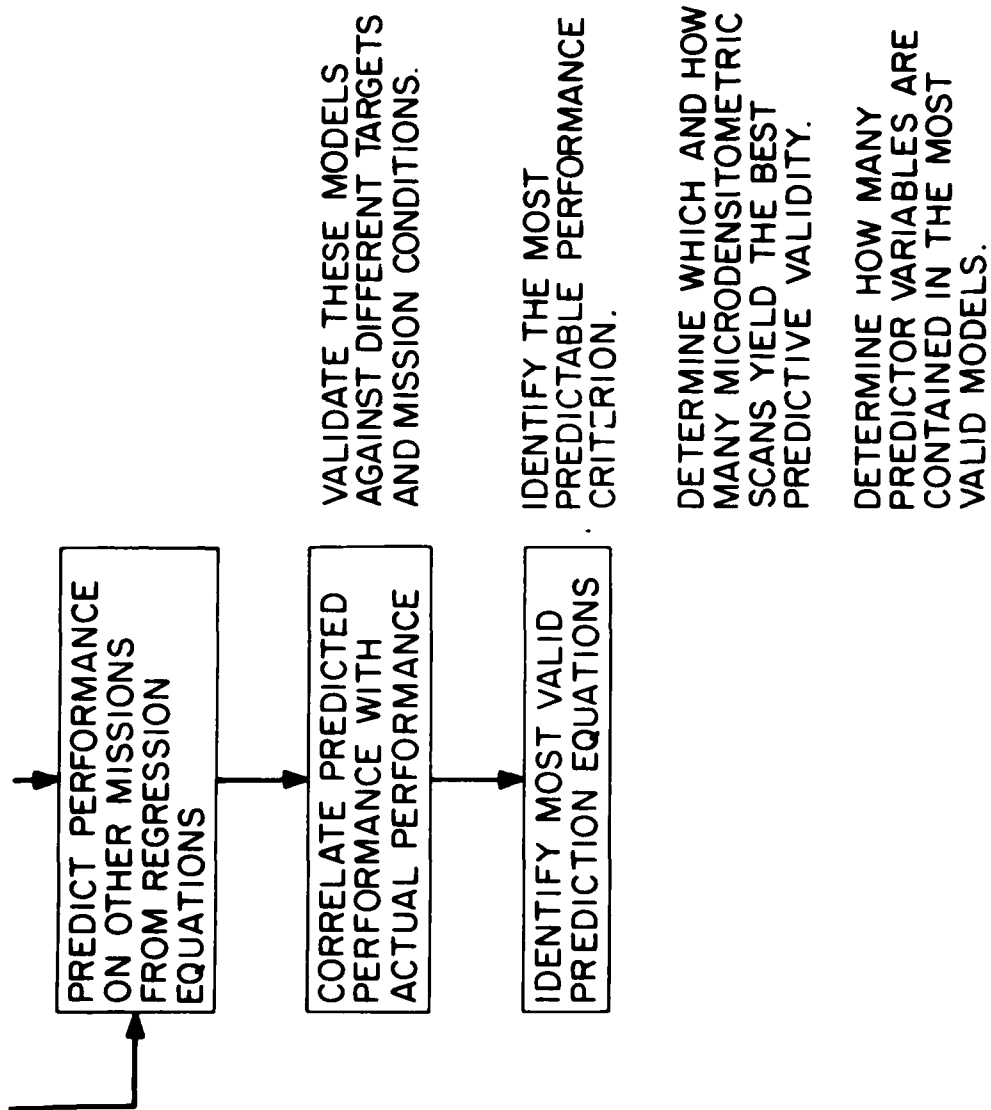


Figure 1 (continued)

The terrain model was filmed with a 75 mm lens. The taking camera field of view was 14.2° horizontal by 18.8° vertical. The same path was followed along the terrain model and a constant simulated altitude of 10,000 ft was maintained in making all three films. They differ only in the boresight depression angle of the camera and simulated groundspeed, as follows:

<u>Film number</u>	<u>Groundspeed (ft/sec)</u>	<u>Depression angle (from horizontal)</u>
43	500	45°
76	500	23°
77	3,000	23°

Films 76 and 77 differ only in simulated groundspeed; thus, for any single frame appearing on Film 77, there is an identical frame on Film 76 and microdensitometric scans across the two corresponding frames are also identical. Stated another way, because of the 6:1 groundspeed ratio, every frame from Film 77 corresponds to every sixth frame from Film 76. Accordingly, at a playback speed of 30 frames/sec, a target presented on Film 77 will be "in view" only one-sixth as long as the same target on Film 76.

The Autonetics researchers identified 66 targets appearing in each mission and described their location, size, and inherent contrast (using a photopic luminosity criterion). Fifteen of these targets were selected for investigation in previous studies in the VPI&SU Human Factors Laboratory. Targets whose location could be largely determined by contextual cues (a dam, for instance) were ineligible. The targets chosen for use in the VPI&SU experiments are described in Table 1.

Performance (Criterion) Measure Experiments

Human performance data in the acquisition of individual targets were obtained in two experiments (A/G 3 and Spot Wobble) conducted in the Human Factors Laboratory of VPI&SU. The purpose of the studies was to investigate the ways in which various parameters of the video system used for a reconnaissance mission affect target acquisition performance.

Experiment A/G 3. Subjects viewed Films 43, 76, and 77 on a 17-in. (diagonal) television monitor with an aspect ratio of 3:4 (horizontal:vertical). The viewing distance was 40 in. A block diagram of the equipment is shown in Figure 2.

Each subject studied 2 x 3-in. glossy prints of targets extracted from the background until he became familiar with the targets and their names. These photographs, placed in the order of their appearance, were available to the subject for reference throughout the experiment.

Table 1
Target Characteristics

Target number	Target description	Target element		Target/ background contrast
		Length (ft)	Width (ft)	
1 ^a	convoy of 5 missile vans	37	15	0.189
4 ^a	11-unit train	85	21	0.375
9	4 POL tanks	340 diameter		0.603
13	6 small buildings	45	30	0.396
17	2 large buildings	129	65	0.396
21	6 POL tanks	75 diameter		0.603
22	3 large buildings	70	60	0.559
26	airport	4,212	792	0.401
32	construction yard	1,000	875	0.550
36	SAM site	340 diameter		0.414
40	6 ammo bunkers	66	32	0.662
46 ^b	5 small buildings	48	30	0.257
50 ^a	convoy of 5 missile vans	37	15	0.750
53 ^b	SAM site	340 diameter		0.324
61 ^b	9 ammo bunkers	60	32	0.414

^aPredictor variables unobtainable from Films 43 and 76.

^bPredictor variables unobtainable from Film 76.

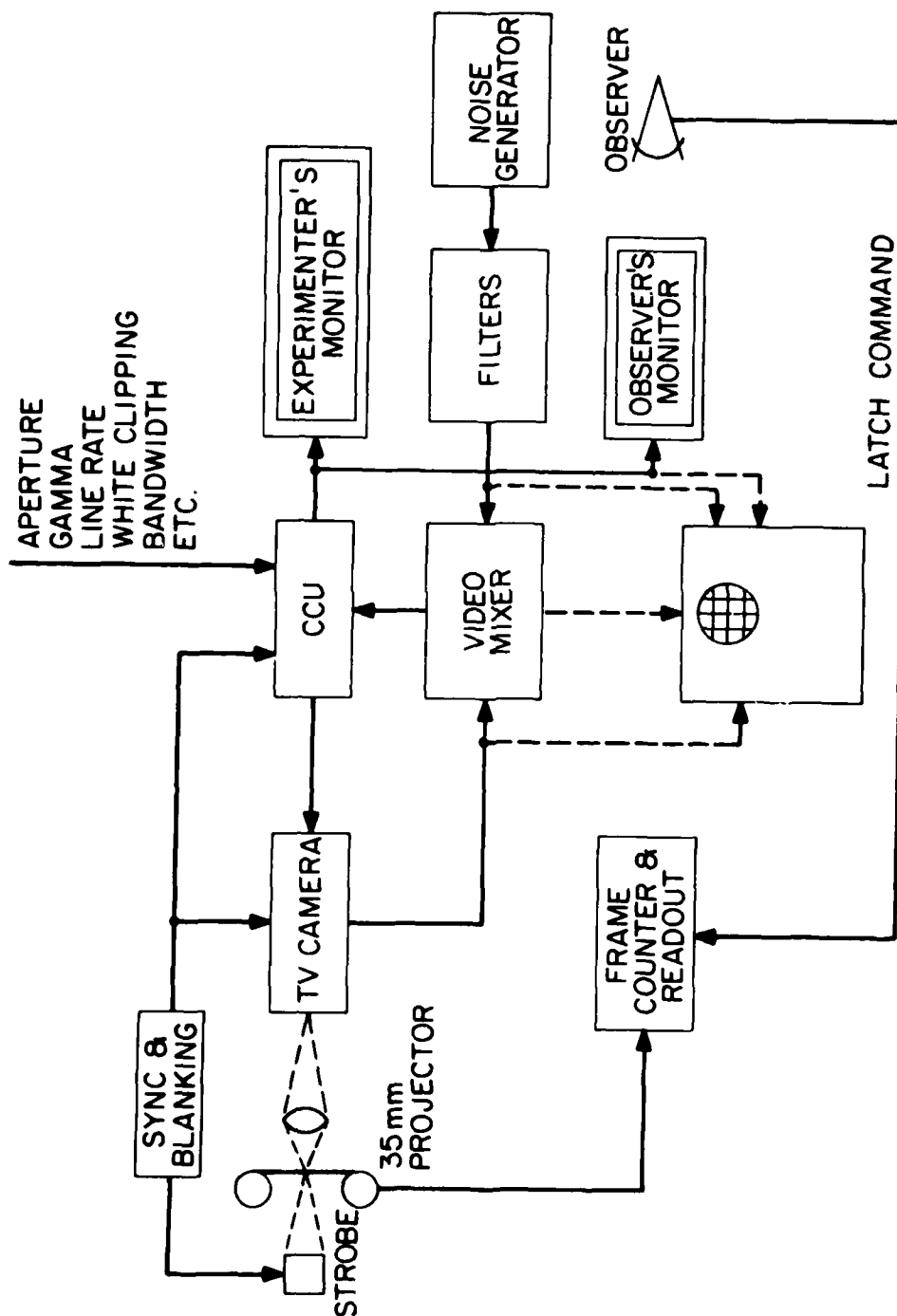


Figure 2. Block diagram of visual display.

The subject viewed each film mission, searching for one specified target at a time. He knew at all times which target would appear next. The subject was informed when each prebriefed target left the field of view so that he could begin searching for the next one. He pushed a hand-held response button when he believed he had found the designated target, and indicated verbally in which fourth of the display he saw the target.

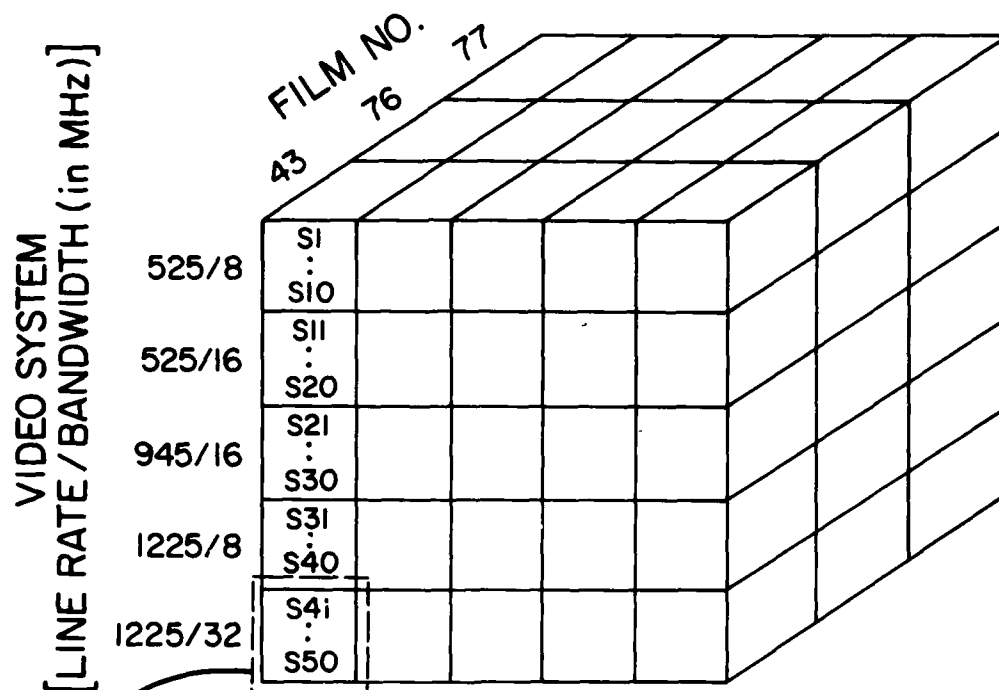
A print-out counter automatically recorded the number of the 35 mm film frame appearing on the screen at the time of the subject's response; this number was later converted to the ground range (in ft) to the target at the time of response. If the target was in the appropriate fourth of the field of view when the subject responded, the response was considered correct. Otherwise, it was recorded as incorrect. On trials in which no response was made (that is, the subject neither found the target nor believed he had), "no response" was recorded. (In the data analysis, "no response" trials were treated in the same manner as "incorrect responses." Hereafter "incorrect response" (IR) refers to both incorrect and no response trials.)

The dependent variables were ground range at acquisition and probability of a correct response. The independent variables of A/G 3 were: reconnaissance mission (Films 43, 76, and 77, which simulate different groundspeeds and depression angles); video system (as defined by line rate/bandwidth combinations); and noise (introduced deliberately into the video system--not present on the film itself).

The experimental design is illustrated in Figure 3. The respective noise levels indicated are judged visually equivalent for all five video systems. One of the 75 cells of the experimental design is enlarged in order to demonstrate a sample distribution of targets over subjects. In each condition, each target was presented twice, once to each of two different subjects.

The major intent of Experiment A/G 3 was to study the effects of video noise on target acquisition. Initially, each video system was analyzed separately; analyses of variance were performed on each of the five systems, using range to the target at acquisition as the criterion.

In the first series of analyses only correct responses were of concern; the mean of a subject's correct responses in a given condition was taken as that subject's cell score. If in a given cell of the experimental design a given subject made no correct responses, the mean of all correct responses (made by other subjects) in that cell was substituted and the appropriate degrees of freedom were subtracted for missing data. The results of these analyses were highly consistent. There was no significant noise level effect and no interaction between noise and film. There was in all cases a highly significant film effect, but this is of little interest and was in fact largely predetermined; since the depression angle of Film 43 is greater than that of Film 76 or 77, the ground range at acquisition is typically shorter.



525/8	0	5	10	25	50
525/16	0	5	10	25	50
945/16	0	5	10	25	50
1225/8	0	2.5	5	12.5	25
1225/32	0	5	10	25	50

NOISE LEVEL (in mV) BY VIDEO SYSTEM

TARGETS

	1	4	9	13	17	21	22	26	32	36	40	46	50	53	61
41	-*					-						-			
42		-					-					-			
43			-					-					-		
44				-					-					-	
45					-					-					-
46	-					-					-				
47		-					-					-			
48			-					-					-		
49				-					-					-	
50					-					-					-

*-INDICATES THIS SUBJECT WAS INSTRUCTED TO SEARCH FOR THIS TARGET.

Figure 3. Experimental design of A/G 3.

In the second series of analyses, the incorrect responses were taken into account. If a subject made an incorrect response (or no response), the ground range at acquisition was considered zero. Otherwise the analyses were conducted as described above, but it was not necessary to adjust the degrees of freedom. (There were no "missing" data because zeros were inserted.) A significant noise effect emerged from this treatment of incorrect response. No significant noise x film interactions were found.

A further analysis was performed across video systems at the zero noise level only. No significant differences were found among video systems, regardless of whether incorrect responses were included.

In summary, noise level had a significant effect on target acquisition performance only if the ground range at acquisition was considered zero in the event of an incorrect response. The five video systems (combinations of line rate and bandwidth) had no differential effect on performance. Effects of varying the speed and depression angle of the film were consistently large.

A/G 3 Performance Measures Used in the Present Study. The film effect was of no consequence to the present study, since the targets appearing in each film were treated as random samples from separate target populations. Performance criteria were established for individual targets on each film by computing mean performance scores across subjects, video systems, and, in some cases, noise levels.

Since no performance differences were found across video systems, using means across this dimension is reasonable. However, there was some evidence that noise introduced into the video system reduced target acquisition performance. Since this noise is not present in the film itself (and microdensitometric scans of the film do not indicate its presence), some criteria were based on the zero noise level alone, or on 10 trials per target.

It was suspected that inclusion of the other 40 trials per target, in which noise was present, would result in a greater stability in criteria which would outweigh the increasing variability effects of noise. That is, a mean across 50 trials may be more reliable than one across 10, although those 50 trials were presented under five different noise levels. Thus, two types of performance criteria were computed for each target on Films 43 and 76--one based only on zero noise and one based on all five noise levels.

(The performance criteria used in the present study from Film 77 of A/G 3 were added after initial regression analyses were conducted. By then it was clear that criteria based only on zero noise are less reliable than those based on all noise levels combined, as deduced from consistently lower correlations between predictors and these criteria. Therefore, the criteria based on zero noise only were not included for Film 77.)

Experiment Spot Wobble. Target acquisition data for targets on Film 76 were also available from a study of the effects of spot wobble and viewing distance (Beamon, 1974). Spot wobble is an electronic technique used to defocus the "raster" lines of a television display.

The subject's task was identical to that in Experiment A/G 3 and target acquisition was defined and recorded in the same manner. The TV monitor was smaller (15 in.), but the vertical aspect ratio was the same (three horizontal to four vertical).

Three viewing distances (18, 36, and 54 in.) and four spot wobble levels (0, 33, 100, and 500 mV) were investigated in a factorial design (Figure 4).

The spot wobble effect was statistically significant due to an improvement in target acquisition performance at the highest level (550 mV) of spot wobble. The 550 mV spot wobble condition was therefore not included in computing performance criteria for the present experiment.

The performance criterion for each target was taken as the mean across six subjects in each of three viewing distance conditions and three spot wobble levels; these criteria were thus based on 54 trials.

Treatment of Incorrect Responses. So far, the sources of six criteria have been discussed:

1. Film 43, A/G 3--zero noise only;
2. Film 43, A/G 3--all five noise levels;
3. Film 76, A/G 3--zero noise only;
4. Film 76, A/G 3--all five noise levels; and
5. Film 77, A/G 3--all five noise levels
6. Film 76, Spot Wobble--no noise, three spot wobble levels.

Three plans of analysis were chosen for each of the six sources listed above, resulting in a total of 18 performance criteria.

Original Plan. The original intention was to use the following criteria of performance (Snyder et al., 1974):

1. The proportion of targets correctly recognized at the zero noise level;
2. The proportion of targets correctly recognized across all five noise levels;
3. The mean ground range of correct recognition at the zero noise level; and
4. The mean ground range of correct recognition across all five noise levels.

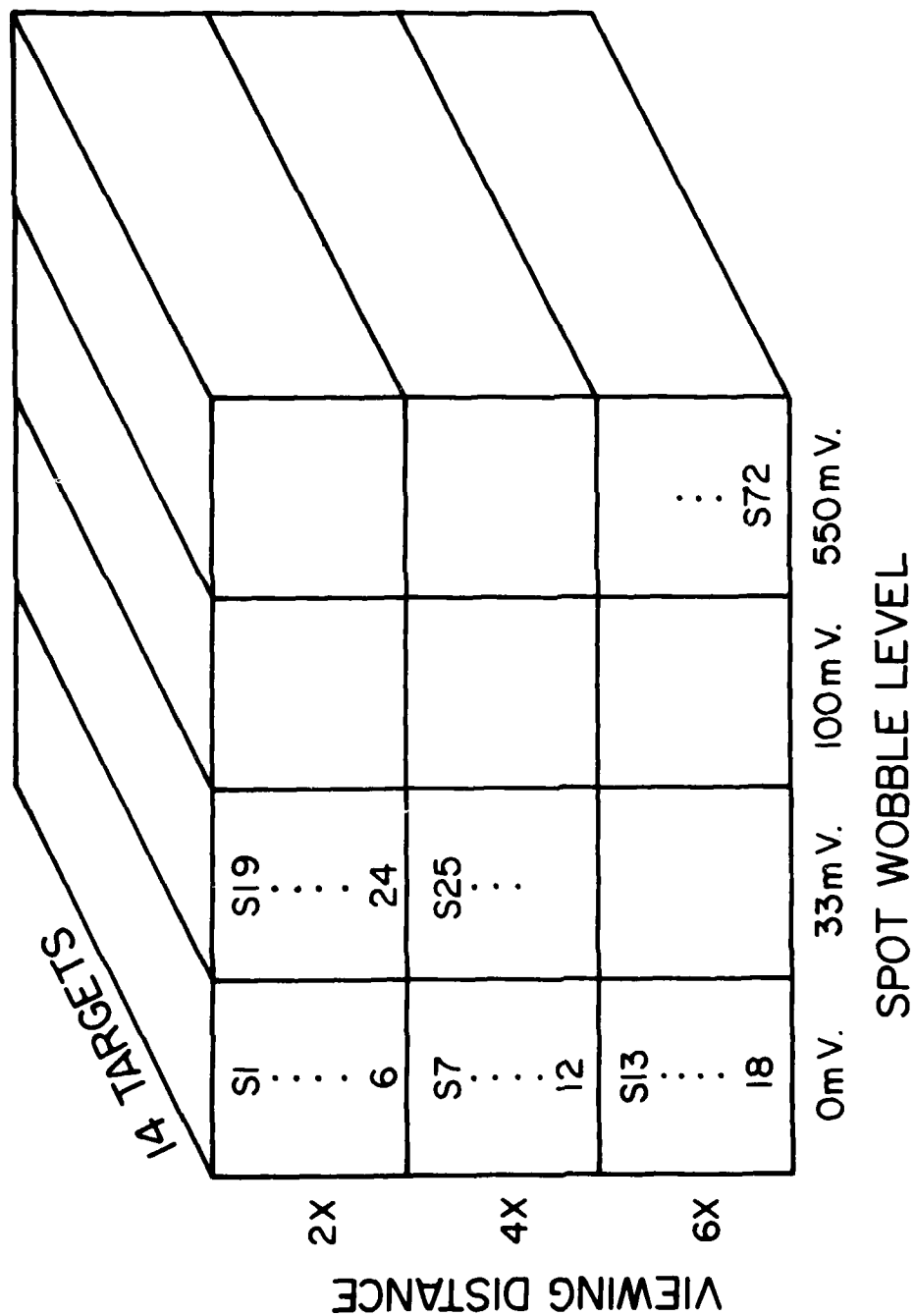


Figure 4. Experimental design of spot wobble.

The performance criteria were computed for the 15 targets of Film 43 according to this plan. It was found that at the zero noise level, there were no incorrect responses to eight of the targets and there were no incorrect responses to six targets at any noise level. Thus, the proportion of correct responses would constitute an insensitive index of target acquisition performance, so criteria (1) and (2) were dropped from consideration. Criteria (3) and (4) were retained. Criteria based on the mean ground range of correct responses only are subsequently labeled CR.

Plan II: Add IR_0 . There is valuable information about target detectability contained in trials which result in incorrect responses. This nonacquisition information should not be ignored.

One metric which incorporates this information and had already proven meaningful in the analysis of Experiment A/G 3 is the mean of all responses, correct and incorrect, and where the ground range of incorrect responses is defined as zero. This criterion was therefore included and this analysis was named CR + IR_0 .

Plan III: Add IR_{min} . The mean ground ranges for correct responses were on the order of 12,000 ft for Film 43 targets and about 25,000 ft for Films 76 and 77. At ground range zero, the target was out of the field of view and had been for some time (Figure 5). Substituting a ground range of zero, then, gives considerable weight to incorrect trials, perhaps too much weight, and certainly a different weight for Film 43 than for Films 76 or 77.

Another meaningful approach to incorrect responses is substituting the ground range at which the target leaves the bottom of the observer's field of view (7,212 ft for Film 43; 15,880 ft for Films 76 and 77). This metric also accounts for nonacquisition, but at the same time takes into account the depression angle of the camera. This criterion is designated CR + IR_{min} , for minimum available range.

Thus, three methods of dealing with incorrect response trials were applied to each of six data bases, to produce a total of 18 criteria. They are listed in Table 2.

Selection of Predictor Variables

Those quantifiable characteristics of an object and its surround which make that object more or less recognizable are not precisely known. It is therefore desirable to investigate any target or background trait which either previous research or intuition may suggest is related to target detectability. For this reason, a relatively large number of predictors--36--were incorporated into this study, although it was known from the start that this number must be drastically reduced in order to be useful in practice. (It is, after all, statistically inappropriate

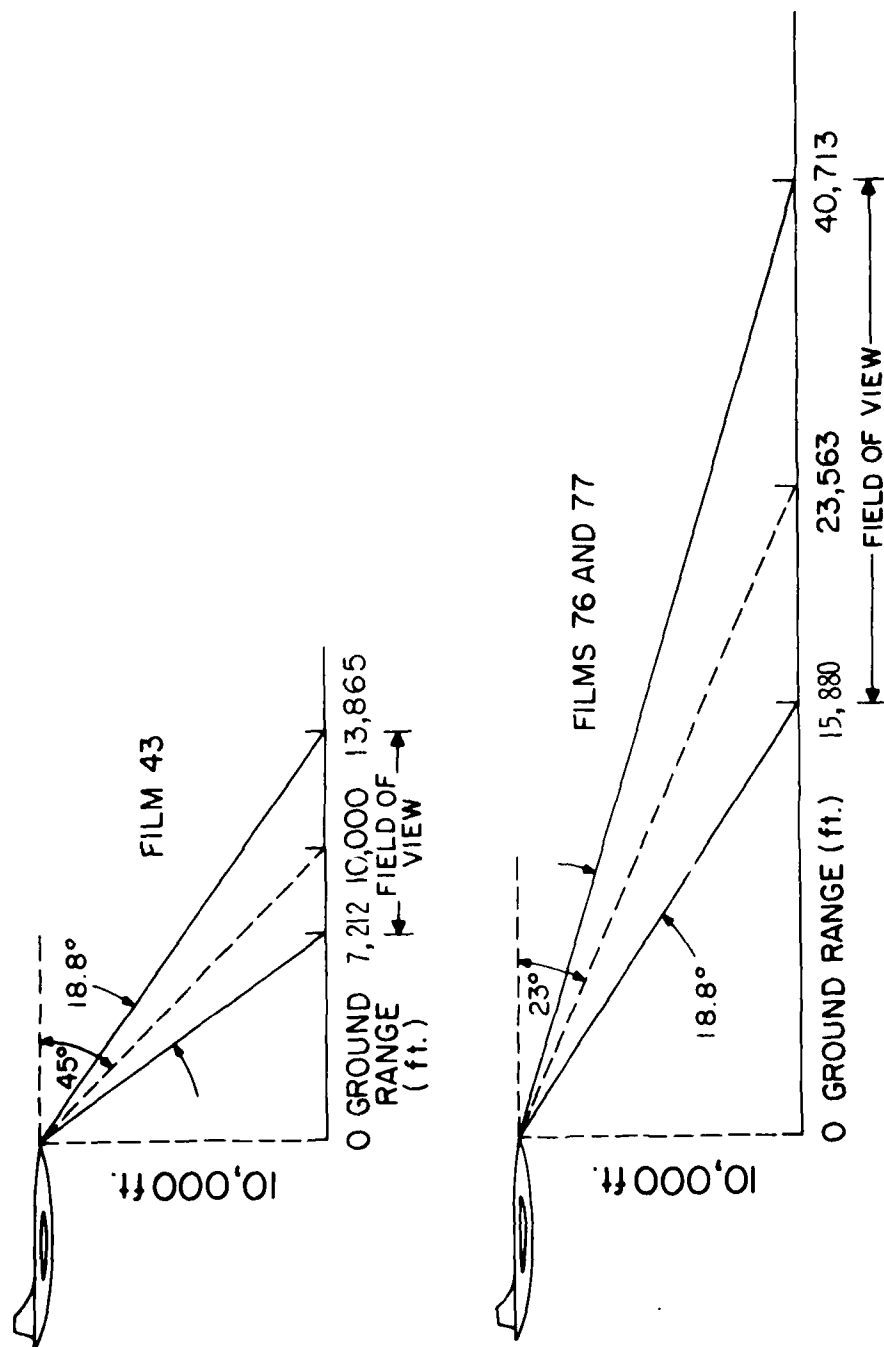


Figure 5. Fields of view.

Table 2

Performance Measures of Target Acquisition

Source of predictors (film)	Source of performance data (experiment)	Number of trials per target	Number of noise levels	Substitution for IR's	Criterion name
43	A/G 3	50	5	Mean	43/5N, CR
43	A/G 3	50	5	Min	43/5N, CR + IR _{min}
43	A/G 3	50	5	Zero	43/5N, CR + IR ₀
43	A/G 3	10	1	Mean	43/ON, CR
43	A/G 3	10	1	Min	43/ON, CR + IR _{min}
43	A/G 3	10	1	Zero	43/ON, CR + IR ₀
76	A/G 3	50	5	Mean	76/5N, CR
76	A/G 3	50	5	Min	76/5N, CR + IR _{min}
76	A/G 3	50	5	Zero	76/5N, CR + IR ₀
76	A/G 3	10	1	Mean	76/ON, CR
76	A/G 3	10	1	Min	76/ON, CR + IR _{min}
76	A/G 3	10	1	Zero	76/ON, CR + IR ₀
76	S.W.	54		Mean	76/SW, CR
76	S.W.	54		Min	76/SW, CR + IR _{min}
76	S.W.	54		Zero	76/SW, CR + IR ₀
77	A/G 3	50	5	Mean	77/5N, CR
77	A/G 3	50	5	Min	77/5N, CR + IR _{min}
77	A/G 3	50	5	Zero	77/5N, CR + IR ₀

to include three to four times more predictors than cases in a regression analysis.)

The choice of predictors was deliberately limited to those which could eventually be derived totally automatically from a preprogrammed scanning apparatus. This condition eliminated all psychophysically determined predictors and left only objective photometric characteristics and a few geometric ones which could be obtained directly from microdensitometric scans and associated computational equipment.

Both target and background parameters were included, as well as measures of their interactions. Some predictors deal with that part of the background immediately surrounding the target. It is reasonable to hypothesize that the target's immediate surroundings are of greatest importance to target detection. Following the precedent of Zaitzeff (1971), the region on either side of the target whose width is 25% of the target's width was chosen for special scrutiny. This area is referred to as 25% background.

Figure 6 illustrates a hypothetical trace across one film frame. The target, background, and 25% background are indicated.

Twenty-three predictor variables were taken directly from the digitized magnetic tape records of microdensitometric scans. Thirteen additional predictors are composites of the first 15. Because of the importance of the selection rationale, each predictor and the rationale for its inclusion are described below.

Although no great predictive power was anticipated of Predictors 1 to 4, they were nevertheless included. Their derivation was necessary for the calculation of other variables, and should any of these variables be shown to predict target acquisition performance with high reliability, their ease of measurement would make them very useful.

1. Mean background luminance (\bar{Y}_{bgd}). The mean transmission from A to C, and from D to F (Figure 6). The value of this metric increases with the average luminance² of the background portion of the film frame.
2. Mean 25% background luminance (\bar{Y}_{25}). The mean transmission from B to C and from D to E.
3. Mean target luminance (\bar{Y}_{tgt}). The mean transmission from C to D, or the average luminance of the target.

² Subjective impressions of these variables are discussed in terms of their appearance on a display (either TV monitor or projected positive image) rather than in the measurement units of the microdensitometer.

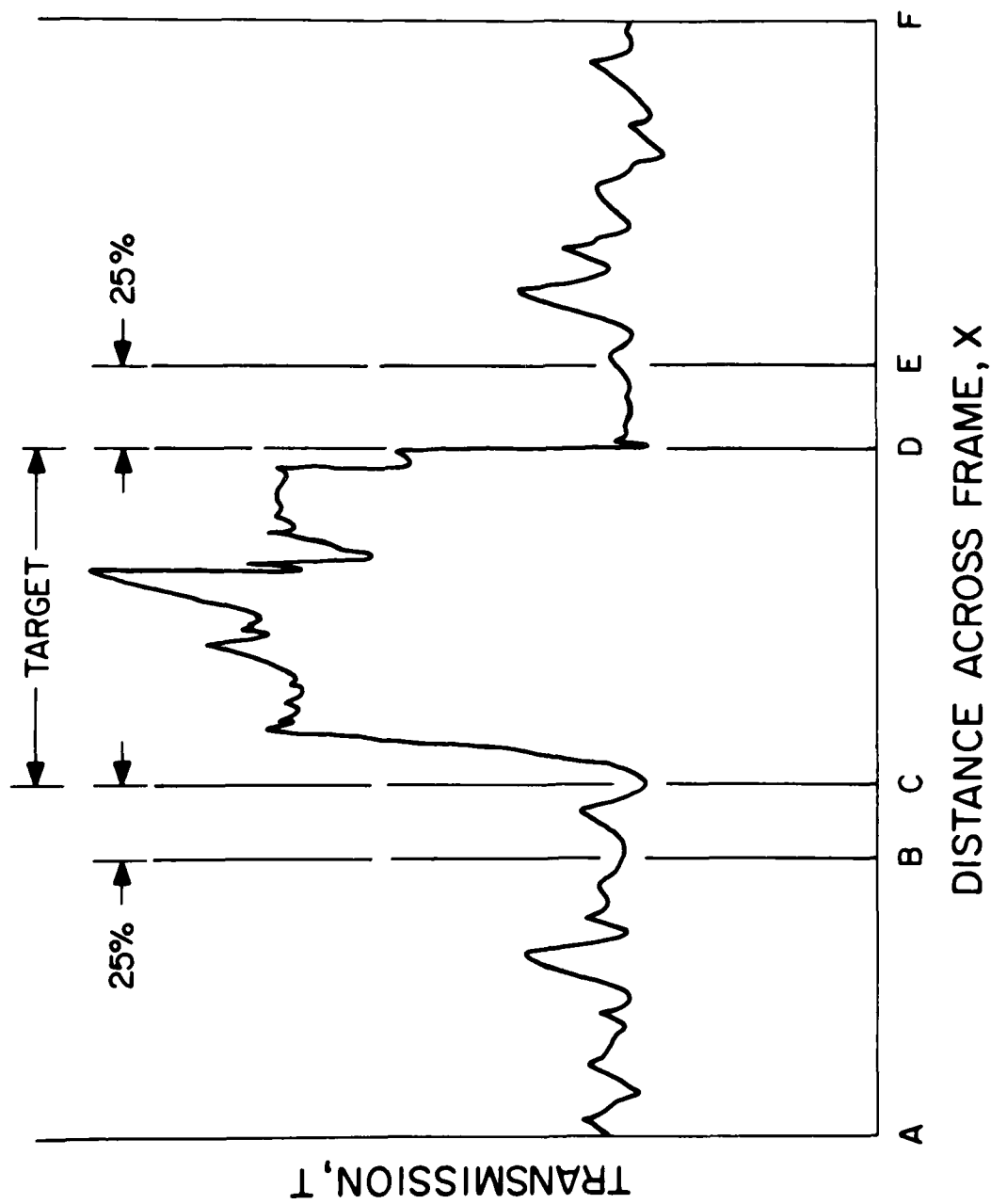


Figure 6. Schematic representation of microdensitometric scanning trace.

4. Mean overall luminance (\bar{Y}_{ov}). The mean transmission from A to F, or the average luminance of the entire scan.

Several measures of scene heterogeneity were included. That "busyness" of the background hampers one's ability to find an object imbedded in the field is intuitively obvious, as well as experimentally substantiated (Corbett et al., 1964; Nygaard et al., 1964; Rhodes, 1964; Zaitzeff, 1971). The best means of quantifying heterogeneity of the scene, however, remains to be established.

The standard deviation about the mean was chosen as one heterogeneity measure. The standard deviation is relatively easy to compute and is independent of the size of each scan segment.

5. Standard deviation of background (σ_{bgd}). The standard deviation of the transmission from A to C and from D to F.
6. Standard deviation of 25% background (σ_{25}). The standard deviation of the transmission from B to C and from D to E.
7. Standard deviation of target (σ_{tgt}). The standard deviation of the transmission from C to D.
8. Standard deviation overall (σ_{ov}). The heterogeneity of the scan as a whole.

Predictors 9 and 10, which are measures of total luminance, were included primarily because their composites were of interest. However, it seemed feasible that Predictor 10 (integrated target luminance), in particular, would be valuable. This metric is effectively the product of target size and mean target luminance; that these two target characteristics should combine meaningfully seems reasonable and is predicted from Ricco's Law (Graham, 1966).

9. Integrated background luminance (ΣY_{bgd}). The integrated transmission from A to C and from D to F.
10. Integrated target luminance (ΣY_{tgt}). The integrated transmission from C to D or, as seen by the observer, the total amount of light reflected from the target.

Predictors 11 and 12 were also used in composite metrics. Even a small detail in the target could increase target detectability if it is either very light or very dark when compared to its surroundings.

11. Maximum target luminance (Max Y_{tgt}). The maximum transmission within the target area (C to D).
12. Minimum target luminance (Min Y_{tgt}). The minimum transmission within the target area.

Target size is clearly related to detectability and has been found to be one of the most useful predictors studied so far (Rhodes, 1964; Zaitzeff, 1971). Several indices of target size are extractable from microdensitometric scans.

13. Target size (Tgt size). The sum across all scans, both horizontal and vertical, of the distance from C to D.

The sum was used instead of a product because this predictor should not be interpreted literally as a measure of area, although if all targets were rectangular and oriented along the vertical or horizontal dimension, the product would be meaningful.

14. Target length (Tgt L). The distance from C to D on a vertical scan.
15. Target width (Tgt W). The distance from C to D on a horizontal scan.

Neither Tgt L nor Tgt W is necessarily the target's major dimension, and Tgt L is not necessarily greater than Tgt W.

A measure of scene heterogeneity, recommended by Corbett et al. (1964), is the frequency with which the luminance changes from lighter than average to darker than average, or vice versa. Operationally defined, this is the number of times the transmission function crosses the mean overall luminance. This metric taps both the frequency and magnitude of changes in luminance and thus serves as a gross index of both the number of details in the scene and the contrast between them.

16. Crosses of mean, background (Cross_bgd). The number of times the transmission function crosses \bar{Y} ov (P4) between A and C, and between D and F.
17. Crosses of mean, 25% background (Cross 25). The number of times the transmission function crosses the overall mean luminance between B and C, and between D and E.
18. Crosses of mean, target (Cross tgt). The number of times the transmission function crosses \bar{Y} ov between C and D.
19. Crosses of mean, overall (Cross ov). The number of times the transmission function crosses \bar{Y} ov from A to F.

A third measure of heterogeneity is the number of times the slope of the transmission function reverses from positive to negative, or vice versa. The magnitude of the change must be at or above the observer's threshold to be meaningful. The number of reversals is the same as the number of local transmission maxima and minima, and is operationally equivalent to Zaitzeff's (1964) "Element Count."

20. Reversals, background (Rev bqd). The number of times the difference between a local maximum and the adjacent local minimum exceeds the assumed luminance difference threshold for visual perception between A and C, and between D and F.
21. Reversals, 25% background (Rev 25). The number of transmission reversals from B to C, and from D to E.
22. Reversals, target (Rev tgt). The number of transmission reversals between C and D.
23. Reversals, overall (Rev ov). The number of reversals between A and F.

The standard deviation is sensitive to the size and luminance difference between adjacent objects. If a scene were composed of one large white area and one large black one, the standard deviation would be maximal. Crosses of the mean is somewhat sensitive to the transmission difference between adjacent objects, but also to the number of such differences. Reversals, on the other hand, measure only the number of suprathreshold details and may therefore be the most "pure" index of scene heterogeneity or complexity.

Regardless of the manner in which heterogeneity is quantified, one would expect high heterogeneity of the background to be detrimental to target acquisition performance.

24. Vertical aspect ratio (L/W). The target's length divided by its width. Expressed in predictor numbers, 14/15.

The significance of vertical aspect ratio is specific to dynamic air-to-ground imagery. At long range, the apparent length of a target is minimal. If the observer's approach path coincides with an elongated target's major dimension, it may not be seen at long range even if it is large. If the same target were approached along its minor dimension, its apparent size would be large even at long range. It was therefore hypothesized that vertical aspect ratio would be negatively related to dynamic target acquisition performance.

Predictors 25 to 32 are indices of the contrast between target and background. The contrast of a target against its background is traditionally defined as: $(\text{mean target luminance} - \text{mean background luminance}) / \text{mean background luminance}$. Modulation has also been shown to be a useful measure of contrast (Cornsweet, 1970), defined as $(\text{mean target luminance} - \text{mean background luminance}) / (\text{mean target luminance} + \text{mean background luminance})$. Thus, modulation is numerically equal to $(\text{contrast} - 1) / (\text{contrast} + 1)$. Modulation is therefore a monotonic, but nonlinear transform of contrast.

Both contrast and modulation can be redefined by substituting the maximum target luminance for the mean to indicate the maximum modulation or contrast between target and background.

If there were little contrast between a target and the background as a whole, but stark contrast between the target and its immediate surrounds, that target may still be highly detectable. Similarly, if the target were considerably lighter than the overall background, but imbedded in a particularly light portion of the background, the target may be very difficult to detect. In order to account for such possibilities, four contrast metrics were included which deal with that area immediately encompassing the target.

Predictors 25 to 28 are measures of mean target modulation and contrast. The numerator is the difference between target luminance and background luminance. Negative values, which would indicate that the target is darker than the background, could have been allowed. However, these predictors were to be combined in a linear prediction model. If negative contrast values were allowed, one would expect a V-shaped function to best describe the relationship between contrast and target acquisition. Typically, thresholds for contrast are independent of algebraic sign (Blackwell, 1946). Therefore, the numerator was defined as the absolute value of the difference in luminance between the target and its background.

- 25. Mean target contrast (Mean tgt Cont). The difference between mean target luminance and mean background luminance divided by mean background luminance. $|3-1|/1$
- 26. Mean target contrast, 25% background (Mean tgt Cont, 25). The same as 25, but with mean 25% background substituted for mean background luminance. $|3-2|/2$
- 27. Mean target modulation (Mean tgt Mod). The difference between mean target luminance and mean background luminance divided by their sum. $|3-1|/(3+1)$
- 28. Mean target modulation, 25% background (Mean tgt Mod, 25). The same as 27, but with mean 25% background luminance substituted for mean background luminance. $|3-2|/(3+2)$

Predictors 29 through 32 indicate the greatest contrast between the background and target. This could be the difference between the background and either the lightest target element or the darkest. Thus, these predictors require alternative definitions. However, it was found in all cases that the difference between the maximum target luminance and the background luminance was greater than the difference between the minimum target luminance and the background luminance. Target number 32 on Film 43 provides an example of this phenomenon. The target area consists of a large, dark yard surrounding white buildings. Y bgd (747) is greater than Y tgt (563). However, a white building (Max Y tgt = 1782)

shows greater contrast to the background than does the darkest portion of the yard ($\text{Min } Y \text{ tgt} = 211$).

29. Maximum target contrast (Max tgt Cont). The difference between maximum target luminance and mean background luminance divided by mean background luminance, or the difference between minimum target luminance and mean background luminance divided by mean background luminance, whichever is greater. $(11-1)/1$, or $(1-12)/1$
30. Maximum target contrast, 25% background (Max tgt Cont, 25). The same as 29, but with mean 25% background luminance substituted for mean background luminance. $(11-2)/2$, or $(2-12)/2$
31. Maximum target modulation (Max tgt Mod). The difference between maximum target luminance and mean background luminance divided by their sum, or the difference between minimum target luminance and mean background luminance divided by their sum, whichever is greater. $(11-1)/(11+1)$, or $(1-12)/(12+1)$
32. Maximum target modulation, 25% background (Max tgt Mod, 25). The same as 31, with mean 25% background luminance substituted for mean background luminance. $(11-2)/(11+2)$, or $(2-12)/(12+2)$

The heterogeneity of a target and its background may somehow interact. Perhaps the more heterogeneous the background, the more homogeneous the target must be in order to "contrast" with its surroundings. The following two predictors are based on this speculation.

33. Ratio of target to background standard deviation ($\sigma_{\text{tgt}}/\sigma_{\text{bgd}}$). The standard deviation of the target divided by the standard deviation of the background. 7/5
34. Ratio of target to 25% background standard deviation ($\sigma_{\text{tgt}}/\sigma_{25}$). The standard deviation of the target divided by the standard deviation of 25% background. 7/6

Predictors 35 and 36 compare the total amount of light reflected from the target to that reflected from the background. They are different from Predictors 25 and 27 in that they include a target size component. Corresponding predictors using the 25% background were not included because the target size component would not be present and the resulting predictors would be exactly equivalent to Predictors 26 and 28, since the size of the 25% background is by definition proportional to target size.

35. Integrated target contrast (Int tgt Cont). The difference between integrated target luminance and integrated background luminance divided by integrated background luminance. $(9-10)/9$

36. Integrated target modulation (Int tgt Mod). The difference between integrated target luminance and integrated background luminance divided by their sum. $(9-10)/(9+10)$

Predictors 35 and 36 may be somewhat confusing in that their names imply that a positive relationship with target acquisition should be anticipated. Actually, a negative correlation should exist, if any. Integrated target luminance (10) is typically very small compared to integrated background luminance (9). Therefore, as 10 increases, $(9-10)$ decreases, as do $(9-10)/9$ and $(9-10)/(9+10)$.

Table 3 summarizes the 36 predictor variables and their previous usage in the literature.

Predictor Sets

A secondary purpose of this study was to determine how much microdensitometric information is needed for the calculation of predictor variables which are reliably related to target acquisition performance. Presumably, the most thorough microdensitometric analysis of a target and its background would yield the most reliable predictor variables and consequently the most valid prediction equation. For example, if an extremely large number of scans were made through each frame containing the target, we could determine the exact size of the target, the exact contrast of the target to the background, and so on. However, the microdensitometric scanning procedure is time-consuming with state-of-the-art equipment. Further, this approach requires extensive data storage and computation capability. It would therefore be useful to know whether increasing, within practical limitations, the number of scans through a scene, or increasing the number of frames which are scanned, substantially improves our ability to predict a target's detectability.

It was assumed that a reasonable sample of the photometric properties of a scene would require a minimum of two microdensitometric scans through that scene: one horizontal and one vertical scan passing through the target's center. Two orthogonal scans were considered necessary in order to (1) reduce the chance of sampling an extremely unrepresentative segment of the background and (2) reduce the chance that the target's orientation would strongly bias the target information sampled. Assume, for example, (1) that a target's major dimension is several times greater than its minor dimension, (2) the major dimension is vertically oriented, and (3) the predictor variables are based upon a single horizontal scan through the target. Then the value of any predictor variable which contains a target size component would constitute a severely biased estimate of the target's true photometric and geometric characteristics.

Table 3
Predictor Variables

Predictor Number	Name	Computational formula	Similar to predictor	Studied by
1	\bar{Y} bgd			
2	\bar{Y} 25			
3	\bar{Y} tgt			
4	\bar{Y} ov		Mean brightness	1
5	σ bgd			
6	σ 25			
7	σ tgt		Detail contrast	4
8	σ ov		σ^2 of brightness	1
			Overall contrast	3
			Scan variance	4
9	ΣY bgd			
10	ΣY tgt			
11	Max Y tgt			
12	Min Y tgt			
13	Tgt Size		Target area	3,4
			Target size	2
14	Tgt L		Target length	4
15	Tgt W		Target width	4
16	Cross bgd		(Suggested by)	2
17	Cross 25			
18	Cross tgt		Detail contrast	4
19	Cross ov			
20	Rev bgd			
21	Rev 25			
22	Rev tgt		Detail contrast	4
23	Rev ov		Element count	1,4
			Amt. of picture detail	3
24	L/W	14/15		
25	Mean tgt Cont	$3-1/1$		
26	Mean tgt Cont, 25	$3-2/2$		
27	Mean tgt Mod	$3-1/(3+1)$		
28	Mean tgt Mod, 25	$3-2/(3+2)$		
29	Max tgt Cont	$(11-1)/1$ or $(1-12)/1$	μ_t/μ_T	2
30	Max tgt Cont, 25	$(11-2)/2$ or $(2-12)/2$	Target contrast	3,4
31	Max tgt Mod	$(11-1)/(11+1)$ or $(1-12)/(1+12)$		

Table 3 (continued)

<u>Predictor</u>		Calculational formula	Similar to predictor	Studied by
Number	Name			
32	Max tgt Mod, 25	$(11-2)/(11+2)$ or $(2-12)/(12+2)$		
33	σ tgt/ σ bgd	7/5		
34	σ tgt/ σ 25	7/6	σ^2 tgt/ σ^2 25	4
35	Int tgt Cont	$(9-10)/9$		
36	Int tgt Mod	$(9-10)/(9+10)$		

¹ Nygaard et al., 1964.

² Corbett et al., 1964.

³ Rhodes, 1964.

⁴ Zaitzeff, 1971.

A larger, and possibly more representative, sample of a scene's microdensitometric properties can be obtained by passing multiple horizontal and vertical scans through the target. Three such scans were made of each dimension of each frame. The target was divided into fourths in each dimension, as seen in Figure 7. Solid lines indicate the location of scanning paths.

More than three scans of each dimension could not be practically accomplished, as some targets were so small that more than three discrete and replicable scanning paths could not be identified. Each frame, then, was scanned a total of six times, three horizontal and three vertical.

In dynamic viewing, a target's appearance changes as it is approached; the apparent luminance and size increase, and details become more distinguishable. Further, no single frame of a motion picture film contains the entire background which might be relevant to locating a given target.

In order to determine whether the power of predictors can be augmented by using multiple frames containing the target, two frames corresponding to two different target distances were scanned. In the first frame, the target was located in the (vertical) center of the field of view. On Film 43 this meant that the ground range to the target's center was 10,000 ft.; on Films 76 and 77 the ground range was 23,563 ft.

Six additional scans were taken through the frame in which the target was halfway between the center of the field of view and the near edge. (Ground range = 8,481 ft. on Film 43; 19,047 ft. on Films 76 and 77.) Frame numbers corresponding to these target locations were computed, and the appropriate frames were extracted from each filmstrip for scanning.

Four sets of predictor variables were computed for each target on each film. Each predictor set was based upon varying amounts of microdensitometric information:

1. Two frames, six scans/frame (Predictor Set 2/6). Predictor variables were computed on the basis of all 12 available scans, three vertical and three horizontal scans on each of two frames.
2. One frame, six scans/frame (Predictor Set 1/6). Predictors were based upon the first frame, in which the target was centrally located. All six scans of that frame were used in computing this set of predictor variables.

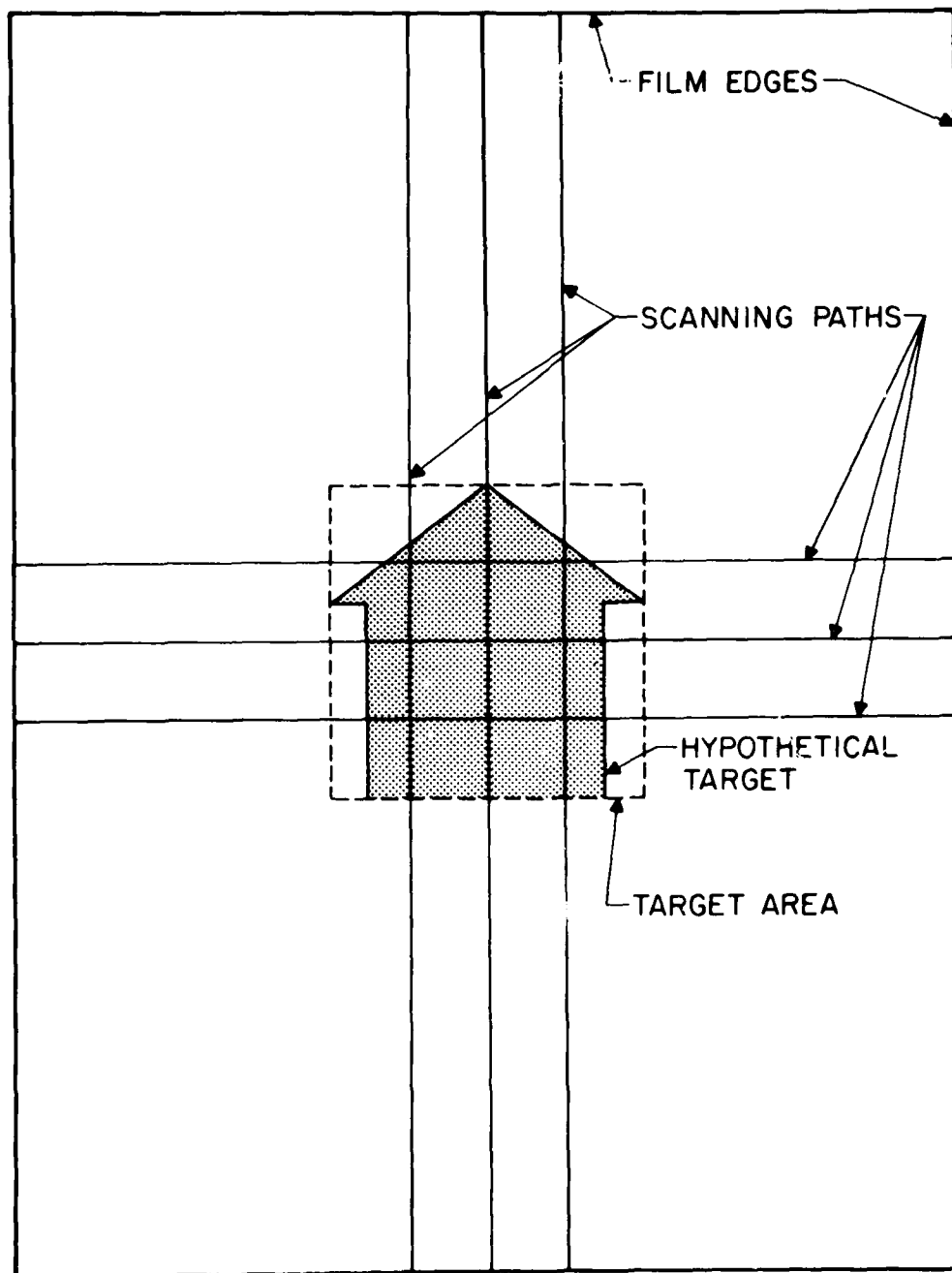


Figure 7. Vertical and horizontal scanning paths.

3. Two frames, two scans/frame (Predictor Set 2/2). Both frames were used, but only the two scans (one vertical and one horizontal) passing through the target's center on each frame were considered; thus, four scans were included.
4. One frame, two scans/frame (Predictor Set 1/2). Predictor variables were calculated from the two center scans (one vertical, one horizontal) of the center frame.

Microdensitometric Data Collection Procedure

A block diagram of the equipment used in collecting the microdensitometric scans is shown in Figure 8. The function performed by each item of equipment is briefly described below.

Microdensitometer. The microdensitometer used in this experiment was the Gamma Scientific Model 700-10-80. Basically, it has a light source in the bottom, the image of which is focused as a 60-micron spot in the film plane. A 2.5x magnifying objective lens, coupled with a magnifying eyepiece, permits sensing of this 60-micron spot with virtually perfect registration of the sensed area and the illuminated spot. The eyepiece contains a 150-micron probe which is directly coupled to a fiber optics rope. The rope leads directly to a photomultiplier tube, which is part of the Gamma Scientific Digital Photometer, Model 2400. The photometer provides a digital readout of the luminance of the spot, which was calibrated to be a direct analog of the luminance of any given area on the television monitor during the experimental trials, as described below. Thus, the digital photometer output could be monitored for calibration and zeroing purposes, while its analog output was used in data collection for this study.

The film holder was driven in one direction by a motor drive unit, which is mounted on the platform of the microdensitometer. The direction of movement of the film plane can be varied, as can be the speed with which the motor drive moves the film frame past the scanning aperture. A potentiometer output on this motor drive provides a DC voltage analog of the motor drive position. This voltage, after amplification, was used to drive an X-Y plotter, Hewlett-Packard Model 7004B, in the X direction.

The analog output from the photometer, representing transmission through the image, was amplified and sent to both the Y-axis of the Hewlett-Packard X-Y plotter as well as to the I.S. Oscar A/D-16 Data Acquisition unit.

A/D-16. The A/D-16 is a custom-made analog sampler and analog-to-digital converter. It has 16 input channels, the combination of which is scanned and converted 2,000 times per second, with each analog input directly converted at this scanning rate (125/sec/channel) to 12 bits of digital resolution. Inputs to this A/D-16 unit were: (1) the

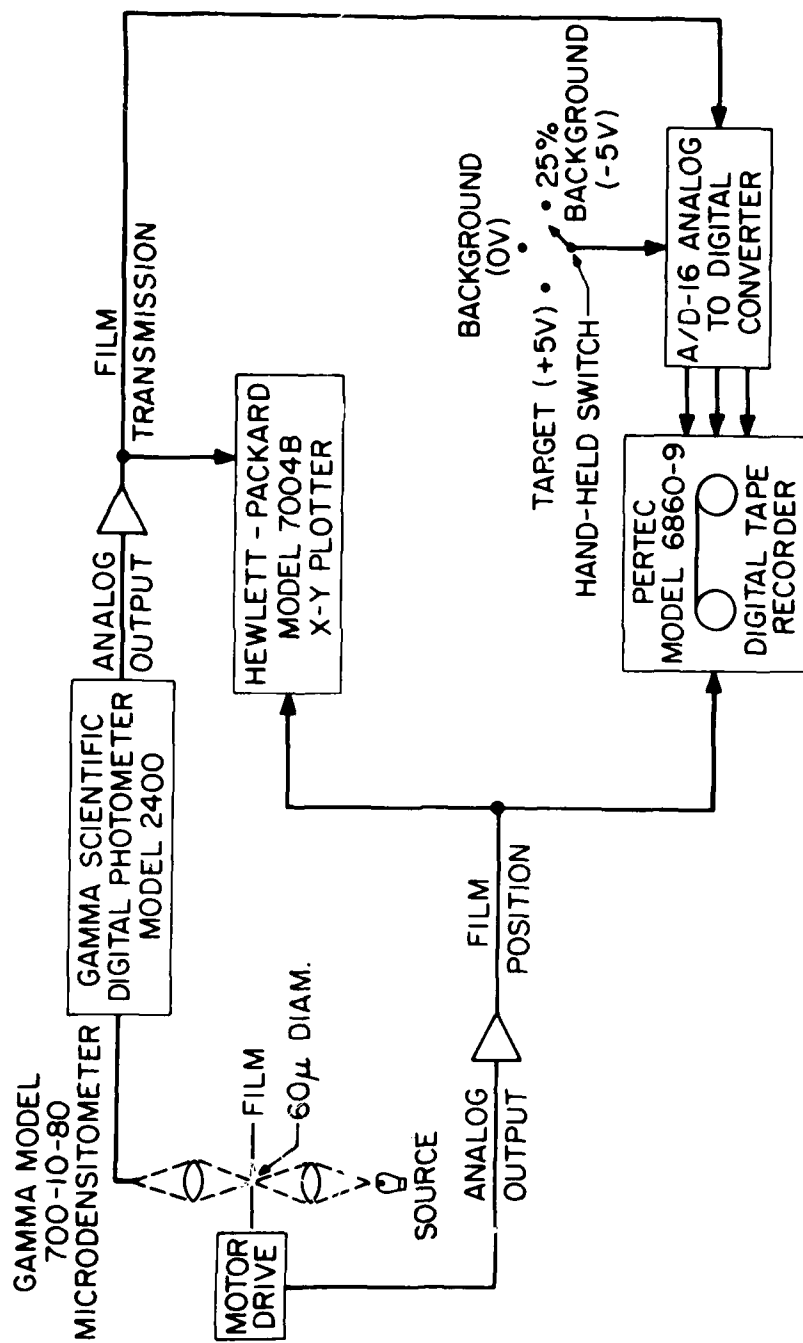


Figure 8. Scanning equipment.

amplified signal from the motor drive of the microdensitometer, which gave X position within the slide; (2) the Y input, amplified, from the digital photometer, which gave direct transmission through the slide; and (3) a discrete DC signal, set by an experimenter's hand-held switch, which indicated target (+5V), background (0V), and 25% background (-5V) scan segments.

The output from the A/D-16 was recorded directly in digital form on a 12.5 ips, 800 bpi Pertec Model 6860-9 9-track magnetic tape recorder. The magnetic tape recorded in this manner is directly compatible with the University-operated IBM 370 computing system, which performed the subsequent data analyses.

Procedure. At the beginning of each data collection session the photometer was zeroed and calibrated so that its maximum analog output (0.1V) corresponded to approximately 100 ft-Lamberts of luminance on the TV display under the conditions in which the A/G 3 and Spot Wobble operator performance data were obtained. Thus, all obtained data units are traceable to the TV luminance conditions.

A film frame was inserted into a glassless holder and placed on the motor-driven stage. The microdensitometer was focused and the photometer tube optical probe was positioned over the illuminated film-plane spot. The film holder was positioned for the desired scanning path. For small targets this was done visually; for large ones, calibrations on the stage were used. The three-position switch was set on "background." The motor drive and A/D-16 were simultaneously activated.

The position of the film on the stage platform was closely monitored through the microdensitometer's eyepiece so that the proper scan segment position on the switch could be maintained. The time at which the target first passed through the photometer's scanning spot was visually determined. The 25% background scan segment was visually estimated for very small targets; stage calibrations were used for larger ones.

The X-Y plotter was used as a backup recording system and for immediate feedback to the experimenter. For example, if the photometer shutter was accidentally left closed, this was known immediately and corrective action could be taken.

All 16 channels of the A/D-16 converter were recorded. The photometer output was recorded on channels 1 and 3, the motor drive output on channel 2, and the three-position switch output on channel 4. This cycle was repeated for channels 5-8, 9-12, and 13-16, thereby obtaining a composite data conversion rate of 2,000 samples/sec.

Unfortunately, the screw motor drive propels the stage only 10 mm at a time. After 10 mm (approximately 75 sec), the stage platform and recording systems must be stopped while the motor drive reverses. This 10 mm (maximum) period is referred to as a trial.

The dimensions of the exposed area of the film frame are 18 mm horizontal by 24 mm vertical. Thus, each horizontal scan was composed of two trials and each vertical scan of three trials which were subsequently combined for data analysis.

The original plan was to make a total of 12 scans across each of the 15 targets of Films 43 and 76 for which performance data were available. Three of the targets (indicated in Table 1) were so small that the time at which the scan passed through the target could not be accurately determined. Rather than risk the resulting unreliability of virtually all the predictor variables, these three targets were dropped from the study.

An additional problem was encountered with Film 76, which consists of three separate reels. It was found that the image contrast on the last reel was considerably lower than that on the other two--so low, in fact, that targets were altogether invisible when viewed through the magnifying eyepiece of the microdensitometer at this magnification scale. This made it impossible to properly locate scanning paths or to determine which film segment was being scanned. Apparently the film was developed at a lower contrast (gamma) than the other reels. Since reduced contrast undoubtedly affected target acquisition performance (an inspection of performance data for these targets confirmed this), it would be improper to substitute corresponding frames of Film 77 for predicting performance on Film 76 targets. Although it would be proper to relate Film 77 scans to Film 77 performance, this, too was impossible; the same problem was found with the last four targets of Film 77, suggesting that the contrast reduction lay in part in the original exposure conditions, and not only in the prints. Therefore, as indicated in Table 1, only 12 targets could be scanned from Film 43 and 9 from Film 76.

The microdensitometric scans of Film 43 targets were stored on nine 2,400-ft magnetic tapes. An additional six tapes were required for Film 76 scans. A total of 144 scans (360 trials) were made of Film 43 targets; 108 scans (270 trials) were made of Film 76 targets.

Tape Conversion

A/D-16 generated tapes are not FORTRAN compatible. The tapes are compatible to the IBM 370 in block length, parity, inter-record gap, and track format, but the data are not compatible with respect to sign conventions, extraneous bits on, and trial delimitation.

The Human Factors Tape Convert Program (Ripley, 1972) reads the A/D-16 generated tapes onto blank magnetic tapes filed in the VPI&SU Computer Center in a FORTRAN-readable format.

All 16 tracks of the A/D converter output were recorded. This means that 1,000 samples of transmission (photometer output) were recorded each second. If each recorded sample were used in computations of predictor variables, a single vertical scan of the target would consist of approximately 225,000 samples. Since the high-resolution TV monitor on which the film was displayed contains a maximum of 1,143 raster lines (and thus, a maximum of about 840 TV lines, or units of resolution), this sample is clearly larger than necessary, as well as computationally uneconomical.

The Human Factors Tape Convert Program has the option of converting only a specified number of channels. For reasons to be discussed below, only the first four channels were read onto the converted tapes. Thus, the original 15 tapes were condensed into four converted tapes.

The converted A/D-16 channels were as follows:

- Channel 1--Y (transmission)
- Channel 2--X (position along scan)
- Channel 3--Y (transmission)
- Channel 4--Scan Segment (background, target, 25% background).

Calculation of Predictor Variables

Channel 2, although recorded, was not used in computations. Since the motor drive maintains a constant speed (verified by plotting motor drive output over time), an equal distance separates adjacent transmission samples.

Channel 3 was also not used. If it had been, an unequal time interval between transmission samples would have resulted. Further, a single channel provides 125 samples/sec, or about 25,000 samples in a vertical scan, far in excess of the display resolution.

Arbitrary units were used in calculating all photometric and geometric variables. The largest number the A/D-16 generates is 2,048. This number was set to correspond to a transmission level equivalent to approximately 100 ft-Lamberts of luminance as displayed on the TV monitor, but no attempt was made to convert to standard photometric units. Rather, transmission (linearly proportional to luminance) was expressed as a value between 0 and 2,048.

The number of samples contained in each segment of the scan (target, 25% background, background) was counted. This number was needed for computing mean transmission and also served as an index of target size.

Two computer programs were developed for the calculation of predictor variables.

Program I. Program I provided all data necessary for the calculation of Predictors 1-15 and 24-36. Each value of Channel 3 was checked to determine whether the accompanying transmission sample fell within the target area, 25% background, or background. Since the 25% background is a subset of the background, these samples were also added to the background. The target samples were similarly added for the computation of "overall" measures.

Two frames containing each target were scanned six times each; four predictor sets, based upon samples contained in 12, 6, 4, or 2 scans, were computed for each target. During data collection, the trials which composed each scan were recorded. Program I summed across all trials composing each predictor set.

The program can be generally described by its inputs and outputs.

Inputs: Program I (FORTRAN statement cards)

Converted magnetic tape

Trial numbers corresponding to each of four predictor sets (data cards)

Outputs: (Printed)

For each trial:³

- (1) Trial number
- (2) Composition (that is, whether 25% bgd or tgt samples are contained in that trial)
- (3) N_t , or the number of samples in each scan segment

For each predictor base:

- (1) N , or total number of transmission samples in each scan segment across all appropriate trials
- (2) ΣY , or sum of all transmission samples in each scan segment across all appropriate trials
- (3) ΣY^2 in each film segment across all appropriate trials

³ Breakdowns by trial were printed to insure that correct trial numbers were listed for each scan and to determine values of Predictors 14 and 15.

- (4) \bar{Y} of each film segment across all appropriate trials $((\sigma Y)/N)$
- (5) σ of each film segment across all appropriate trials $(\sqrt{\Sigma Y^2 - ((\Sigma Y)^2/N)/N})$
- (6) Max Y tgt, or maximum transmission within the target area across all appropriate scans
- (7) Min Y tgt, or minimum transmission within the target area across all appropriate scans.

The values of Predictors 1-8, 11, and 12 were read directly from the computer printout. Integrated luminance was defined as ΣY across all appropriate scans. So that metrics of integrated luminance would be independent of the number of scans comprising the predictor base, ΣY was divided by 6 for Predictor Set 2/6, by 4 for Predictor Set 1/6, and by 2 for Predictor Set 2/2. As a result, ΣY of a given target was similar (although not identical) in each predictor set. These corrected numbers were then divided by 10,000 to reduce the number of digits to a manageable figure. Predictors 9 and 10 were calculated in this manner.

Predictor 13 was calculated as the ratio $N(\text{tgt})/N(\text{ov})$.

Predictor 14 (Tgt L) was calculated from trial printouts. The vertical scans comprising a given predictor set were identified. Target length was the largest $N(\text{tgt})$ of the vertical scans of that predictor set. Predictor 15 (Tgt W) was calculated in the same manner, but in the horizontal dimension.

Predictors 24-36 are composites of Predictors 1-15. They were calculated by hand, according to the formulae shown in Table 3.

Program II. The crosses of the mean and the number of reversals in each film segment were counted in Program II.

A reversal was earlier defined as a difference between a local maximum and its adjacent local minimum which exceeds the luminance difference threshold. This minimum difference was taken as 20 units, or 1% of maximum luminance. (This value assumes that $\Delta L/L = .01$, Weber's constant for luminance.)

In counting both reversals and crosses of the mean, it would be inappropriate to compare 25,000 adjacent points (in the vertical dimension) when the operator performance data were obtained under display conditions having a maximum limiting resolution of about 630 by 840 TV lines.

Therefore, means across several adjacent points were taken to generate a transformed transmission function having approximately as many discrete points as the resolution of the display. The number of adjacent points to combine into a data point was determined as follows.

In the experiments which provided the criterion performance data, the major dimension of the TV display contained an under-scanned 20 mm of the total 24 mm of the film frame, with the cropped portion taken from the top of the film frame. That is, only 20/24 of the total film frame's major dimension was displayed on the TV monitor. However, the microdensitometric scans covered the entire 24 mm in this dimension.

Assuming 840 TV lines (resolution elements) on the display (Snyder et al., 1974) in this major dimension, there are $24/20 \times 840 = 1,008$ potentially resolvable elements on the film frame, or approximately $1,008/2.5 = 403$ potentially resolvable elements per trial.

On the minor dimension of the TV display, one can assume a maximum resolution of 630 TV lines, which displayed the image from a 15 mm wide portion of the 18 mm film frame width. Thus, $18/15 \times 630 = 756$ potentially resolvable elements on the film frame, or approximately $756/2 = 378$ elements per trial.

Thus, to obtain either 403 or 378 elements per trial, one should combine data to produce:

$$\frac{125 \text{ samples/sec} \times 75 \text{ sec/trial}}{403 \text{ (or 378) data points/trial}} = 23.76 \text{ (or 24.80) samples/data point.}$$

To be consistent in both dimensions, and somewhat conservative, 20 samples were averaged to produce each data point.

Program II took 20 transmission samples at a time, computed their mean, stored it, and repeated this cycle until the end of a trial. This vector was then entered into Subroutine PPF (Fung, 1974), which first identified local maxima and minima. If a local maximum was greater than the overall mean luminance, and the adjacent local minimum was smaller, one cross of the mean was counted. If the difference between a local maximum and a local minimum (or vice versa) exceeded 20, a reversal was counted. The total number of such "reversals" was later divided by two to conform to the usual definition of reversals of a function.

The scan segment in which each sample fell was identified as in Program I. For each trial, then, three vectors (one each for target, background, and 25% background) were entered into the subroutine. Sums across trials were computed as before.

Inputs: Program II with Subroutine PPF

Converted magnetic tape

Trial numbers corresponding to scans comprising each
of four predictor sets

\bar{Y} ov corresponding to each trial number

Outputs: For each predictor set:

(1) Crosses of the mean in each scan segment

(2) Reversals in each scan segment

As in Predictors 9 and 10, Crosses (Predictors 16-19) and Reversals (Predictors 20-23) were divided by appropriate constants to result in similar indices across predictor sets.

Whereas portions of the calculations of most of the 36 predictor variables were done on a desk calculator, there is no reason a computer could not be programed to perform all calculations.

After all predictors and criteria were calculated and tabulated, they were punched onto IBM cards in a format compatible with the Bio-medical (BMD) statistical package (Dixon, 1970). There was a total of eight data decks--four predictor sets for each of the two scanned films. Target-by-target predictor and criterion scores are presented in the appendix.

ANALYSIS AND RESULTS

Although it is customary to present analysis procedures and experimental results separately, the sequential nature of model development and validation in this case lends itself more readily to an integrated reporting format. A brief restatement of the purposes of the study will help clarify the rationale of each phase of the analysis.

1. Identify the predictor variables which are consistently and linearly related to target acquisition performance.
2. Combine the "best" predictors into linear prediction equations of target acquisition performance based on Film 43 targets.
3. Validate these prediction equations against targets of Films 76 and 77.

4. Determine how much microdensitometric information is needed for reliable prediction of target acquisition performance.
5. Determine which performance criteria (that is, which technique of defining the ground range at acquisition for incorrect response trials) can be best predicted from a linear combination of photometric and geometric characteristics of targets and their backgrounds.

BMD 2R

The multiple linear stepwise regression program (BMD 2R) of the Biomedical statistical package (Dixon, 1970) was used in several phases of the analysis. The program computes a sequence of multiple linear regression equations using a forward stepwise least-squares method.

The first predictor to enter into solution is the one with the highest product-moment correlation with the criterion. The second variable added has the highest partial correlation with the criterion partialled on the first variable. Equivalently, the variable added makes the greatest reduction in the error sum of squares and has the highest F-value⁴ to enter. This process is continued until the F-value of no additional variables exceeds the specified value of F. If a very low value of F is chosen (i.e., .00001), the process typically continues until all variables are in solution or $R = 1.00$.

A complete Pearson product-moment intercorrelation matrix is printed. Provided at each step are: variable entered, R, regression coefficients, an analysis of variance summary table, and partial correlations of variables not in the equation.

Phase I

As previously indicated, predictors derived from Film 43 can be related to six criteria, and predictors derived from Film 76 imagery are appropriately related to 12 criteria (nine from Film 76 trials and three from Film 77 trials, Table 2). In addition, four predictor sets were computed from each of the two films (43 and 76). This results in 72 combinations of predictor sets and criteria.

⁴The F is not to be confused with the F ratio from the analysis of variance. The BMD 2R F-value is vaguely defined and was therefore set at an extremely small value to permit all variables to enter solution.

All 72 possible multiple linear stepwise regression analyses were first performed; all 36 predictors were allowed to enter into solution. In most cases, R reached .95 in four steps in Film 43 analyses (N = 12); in Film 76 (N = 9) R usually reached .99 in four steps. However, little consistency could be found in the order in which variables entered into solution. For example, in one of the 72 analyses, Predictors 19, 5, 3, and 14 were entered first. In another analysis, Predictors 35, 31, 29, and 24 were "most important."

This result is not surprising. When the number of predictors is large (36) compared to the number of cases (9 or 12), some of those predictors will, by chance, be linearly related to the criterion.

In order to identify those predictors which are consistently related to target acquisition performance, the intercorrelation matrices provided by the initial regression analyses were examined. Twelve of the 18 criteria were arbitrarily chosen for consideration--the six criteria from Film 43, A/G 3 and the six from Film 76, A/G 3. All four predictor sets from each film were inspected. For each predictor variable, four correlations (one per predictor set) with each of the 12 criteria were tabulated.

The mean of the 48 correlational coefficients and the number of negative coefficients were computed for each predictor variable. Results are shown in Table 4.

In a typical correlational analysis a single index of the linear relationship between a predictor and a criterion is obtained. The probability that this correlational coefficient is significantly different from zero (or, conversely, due to chance alone) is estimated from the magnitude (and degrees of freedom) of the correlational coefficient.

But if we have a number of independent indices of the relationship between two variables, a more precise method is available for estimating the "significance" of the relationship. If, over 48 replications, a given predictor is in all cases positively (or negatively) correlated with performance, the probability that the relationship is due to chance alone is 3.55×10^{-15} ($p = 1/2^{48}$)! Although these correlations are not all truly independent of one another, even with some relationships among them, the probability of occurrence of such an extreme combination by chance is considered to be very low.

Seventeen of the 36 predictors passed this "test of consistency." These predictors (indicated in Table 4) were retained for further analyses regardless of the magnitude of their correlational coefficients. A predictor's reliable relationship to performance, even if it is small, can add considerably to the proportion of accountable variance in a multiple regression equation.

Table 4
Summary of Correlations Between Predictors and Criteria
Across 48 Replications

Predictor variable	\bar{r}	Number of negative r's (of 48 possible)
1 \bar{Y} bgd	-.02	12
2 \bar{Y} 25	-.04	18
3 \bar{Y} tgt	.21	6
4 \bar{Y} ov	.24	8
5 σ bgd	.09	12
6 σ 25	.04	23
7 σ tgt	.28	2
8 σ ov	.39	1
9 \bar{Y} bgd	-.23	36
10 ^a \bar{Y} tgt	.57	0
11 ^a Max \bar{Y} tgt	.32	0
12 ^a Min \bar{Y} tgt	.08	15
13 ^a Tgt Size	.58	0
14 ^a Tgt L	.55	0
15 ^a Tgt W	.60	0
16 Cross bgd	-.41	38
17 Cross 25	.31	10
18 Cross tgt	.25	13
19 Cross ov	-.36	35
20 ^a Rev bgd	-.46	48
21 ^a Rev 25	.25	0
22 ^a Rev tgt	.55	0
23 ^a Rev ov	-.27	36
24 ^a L/W	.34	0
25 ^a Mean tgt Cont	.49	0
26 ^a Mean tgt Cont, 25	.61	0
27 ^a Mean tgt Mod	.52	0
28 ^a Mean tgt Mod, 25	.60	0
29 ^a Max tgt Cont	.25	0
30 ^a Max tgt Cont, 25	.26	0
31 Max tgt Mod	.22	2
32 Max tgt Mod, 25	.27	2
33 σ tgt/ σ bgd	.21	2
34 σ tgt/ σ 25	.21	9
35 ^a Int tgt Cont	-.59	48
36 ^a Int tgt Mod	-.61	48

^aRetained for further analyses.

Phase II

In Phase II, a second series of regression analyses was performed on Film 43 targets. Only the 17 retained predictors were allowed to enter solution. The regression equations generated from these analyses served as predictive models of target acquisition.

Phase I intercorrelational matrices suggested that criteria based on all 50 trials (5 noise levels) are more predictable (i.e., reliable) than those based on only 10 trials at zero noise. Zero noise criteria of Film 43 were therefore not used for model development.

Separate regression equations were calculated for each predictor set and each incorrect response definition, for a total of 12 multiple linear stepwise regression analyses. Results are seen in Tables 5 through 8. Shown at each of five steps in the stepwise regression are the variables in solution, their regression coefficients, their beta weights, and R.

The regression coefficients at any given step essentially constitute a linear predictive model of target acquisition performance. For example, the model given at Step 3, Predictor Set 2/6, Criterion CR is:

$$Y' = 12959 + 10204 (P28) - 1151.7 (P30) - 1.4931 (P20) \quad (1)$$

where Y' is a target's predicted ground range at acquisition. Then if Y is the actual mean ground range (value for that target of Criterion 43/5N, CR), .87 is the correlation between Y' and Y across the 12 targets.

The regression coefficient of P30 is negative, even though P30 was shown in Phase I to be positively (though slightly) related to performance. This occurred with other variables as well. P30 (Max tgt Cont, 25) contributes to the multiple correlation by accounting for a large proportion of the variance in P28 (Mean tgt Mod, 25), rather than by correlating highly with the criterion. Thus, by assuming that P30 is a suppressor variable, a negative coefficient is just as likely as a positive one.

Phase III

In Phase III the models of target acquisition generated in Phase II from Film 43 targets were applied to targets on Films 76 and 77 and to different (zero noise) criteria of Film 43 targets.

Table 5
Regression Coefficients for Predictor Set 2/6

Step	Y-Intercept	CR					R
		P(28)	(P30)	P(20)	P(24)	P(27)	
1	8179.0	8179.3 (.666)					.67
2	11917.0	12442.0 (1.013)	-1047.8 (-.578)				.81
3	12959.0	10204.0 (.831)	-1151.7 (-.636)	-1.4931 (-.377)			.87
4	12756.0	8462.7 (.689)	-997.6 (-.551)	-1.9151 (-.484)	441.14 (.248)		.89
5	12226.0	12328.0 (1.00)	-1028.9 (-.568)	-1.5124 (-.382)	998.39 (.560)	-4271.9 (-.481)	.91

Step	Y-Intercept	CR + IR _{min}					R
		P(28)	P(30)	P(22)	P(11)	P(13)	
1	10655.0	10977.0 (.722)					.72
2	11505.0	16043.0 (1.056)	-1245.0 (-.556)				.85
3	11519.0	17938.0 (1.181)	-1308.0 (-.584)	-6.2509 (-.159)			.86
4	9047.0	16302.0 (1.073)	-1208.3 (-.539)	-16.022 (-.407)	1.8445 (.389)		.89
5	9323.0	15055.0 (.991)	-1250.8 (-.558)	-20.030 (-.508)	1.7115 (.361)	-2731.8 (.230)	.89

Note. Beta weights in parentheses.

Table 5 (continued)

Step	Y-Intercept	CR + IR ₀					R
		P(28)	P(30)	P(29)	P(22)	P(25)	
1	9364.0	17098.0 (.663)					.66
2	10881.0	26144.0 (1.045)	-2223.5 (-.585)				.81
3	10425.0	24787.0 (.962)	-2818.7 (-.742)	929.85 (.243)			.83
4	9962.0	31043.0 (1.205)	-3754.4 (-.988)	1988.00 (.519)	-25.723 (-.385)		.85
5	9375.0	40901.0 (1.587)	-5753.9 (-1.514)	4185.90 (1.092)	-39.832 (-.596)	-2850.1 (-.481)	.89

Note. Beta weights in parentheses.

Table 6
Regression Coefficients for Predictor Set 1/6

Step	Y-Intercept	CR					R
		P(26)	P(20)	P(30)	P(29)	P(25)	
1	11354.0	3057.5 (.618)					.62
2	12270.0	2339.5 (.473)	-1.6049 (-.408)				.73
3	12667.0	3326.3 (.672)	-1.8099 (-.459)	-582.77 (-.359)			.78
4	12570.0	3340.1 (.675)	-2.3109 (-.587)	-1839.3 (-1.136)	1259.0 (.828)		.86
5	12300.0	6883.7 (1.391)	-2.2702 (-.576)	-3764.0 (-2.323)	3116.3 (2.049)	-3092.2 (-.927)	.94

Step	Y-Intercept	CR + IR _{min}					R
		P(26)	P(13)	P(30)	P(21)	P(14)	
1	10926.0	3802.8 (.622)					.62
2	10911.0	2520.1 (.412)	4664.2 (.350)				.68
3	11232.0	3495.3 (.571)	5668.9 (.426)	-676.31 (-.337)			.73
4	11576.0	4174.5 (.682)	9971.7 (.749)	-1155.5 (-.577)	-27.101 (-.438)		.79
5	10844.0	4925.3 (.805)	30870. (2.320)	-824.48 (-.411)	-65.985 (-1.067)	-.31665 (-1.517)	.87

Note. Beta weights in parentheses.

Table 6 (continued)

Step	Y-Intercept	CR + IR ₀					R
		P(26)	P(13)	P(30)	P(21)	P(14)	
1	9778.0	5993.8 (.576)					.58
2	9758.0	4231.6 (.406)	6407.2 (.283)				.62
3	10247.0	5715.7 (.547)	7936.2 (.350)	-1029.2 (-.302)			.66
4	10749.0	6704.3 (.644)	14227. (.628)	-1729.8 (-.508)	-39.623 (-.376)		.71
5	9382.0	8112.0 (.780)	53255. (2.353)	-1111.6 (-3.26)	-112.2 (-1.067)	-.5914 (-1.665)	.82

Note. Beta weights in parentheses.

Table 7
Regression Coefficients for Predictor Set 2/2

Step	Y-Intercept	CR					R
		P(15)	P(20)	P(21)	P(27)	P(30)	
1	11553.0	.27678 (.636)					.64
2	12233.0	.20421 (.469)	-1.1550 (-.300)				.68
3	12962.0	.18093 (-.416)	-2.6002 (-.675)	63.076 (.811)			.75
4	12906.0	.21979 (-.505)	-2.6388 (.685)	52.675 (.677)	2223.9 (.284)		.78
5	12888.0	.00535 (.012)	-2.1250 (-.552)	22.672 (.291)	3465.5 (.442)	-530.33 (-.361)	.81

Step	Y-Intercept	CR + IR _{min}					R
		P(27)	P(20)	P(21)	P(22)	P(35)	
1	10873.0	7080.4 (.689)					.69
2	11541.0	6515.1 (.634)	-1.3369 (-.264)				.74
3	11456.0	4286.2 (.417)	-1.3475 (-.267)	30.340 (.297)			.76
4	11323.0	5228.8 (.509)	-1.1531 (-.228)	97.967 (.960)	-33.599 (-.789)		.82
5	17252.0	5757.9 (.561)	-.93148 (-.184)	87.048 (.853)	-39.424 (-.925)	-6252.4 (-.233)	.83

Note. Beta weights in parentheses.

Table 7 (continued)

Step	Y-Intercept	CR + IR ₀					R
		P(15)	P(30)	P(36)	P(14)	P(35)	
1	10182.0	.53629 (.587)					.59
2	10712.0	.72561 (.794)	-1001.1 (-.324)				.64
3	25297.0	.03670 (.040)	-2968.3 (-.963)	-13452. (-1.302)			.72
4	35671.0	-.08870 (-.097)	-2789.5 (-.905)	-24640. (-2.385)	0.34798 (-1.032)		.74
5	12738.0	.94946 (1.039)	-3616.9 (1.173)	-88342. (-8.552)	-2.3056 (-6.839)	85946. (2.004)	.81

Note. Beta weights in parentheses.

Table 8
Regression Coefficients for Predictor Set 1/2

Step	Y-Intercept	CR					R
		P(20)	P(21)	P(28)	P(22)	P(24)	
1	13240.0	-2.3043 (-.616)					.62
2	13001.0	-2.5880 (-.692)	27.830 (.514)				.80
3	13731.0	-4.5482 (-1.217)	171.74 (3.172)	-13472. (-2.665)			.90
4	13584.0	-4.2954 (-1.149)	201.28 (3.718)	-10507. (-2.078)	-26.463 (-1.148)		.93
5	13229.0	-4.0707 (-1.089)	232.87 (4.301)	-11420. (-2.259)	-37.948 (-1.647)	276.35 (.298)	.96

Step	Y-Intercept	CR + IR _{min}					R
		P(15)	P(20)	P(21)	P(28)	P(22)	
1	11158.0	.40996 (.622)					.62
2	11986.0	.33575 (.509)	-1.4969 (-.324)				.69
3	13274.0	.24763 (-.375)	-3.5205 (-.762)	59.179 (.884)			.75
4	13057.0	.35411 (.537)	-4.6183 (-1.000)	233.51 (3.490)	-21461. (-3.436)		.88
5	11595.0	.98109 (1.488)	-2.7666 (-.599)	304.20 (4.547)	-20546. (-3.275)	-59.959 (-2.106)	.93

Note. Beta weights in parentheses.

Table 8 (continued)

Step	Y-Intercept	CR + IR ₀					R
		P(15)	P(20)	P(21)	P(28)	P(22)	
1	10190.0	.62289 (.555)					.56
2	11144.0	.53737 (.479)	-1.7249 (-.219)				.59
3	13238.0	-.41136 (-.366)	-5.0157 (-.638)	96.241 (.845)			.65
4	12846.0	.67608 (.603)	-6.9996 (.891)	411.27 (3.614)	-38783. (-3.650)		.81
5	10123.0	1.8438 (1.644)	-3.5507 (-.452)	542.94 (4.772)	-36910. (-3.474)	-112.69 (-2.306)	.88

Note. Beta weights in parentheses.

For each predictor set and IR definition there are five models of target acquisition, each combining 1, 2, 3, 4, or 5 predictors into a linear prediction equation. An example will demonstrate which models are applicable to which predictor sets and criteria.

Models developed from Film 43 targets (Predictor Set 2/6, Criterion 43/5N, CR) were applied to Film 43 targets (Predictor Set 2/6, Criterion 43/ON, CR) and to Film 76 and 77 targets (Predictor Set 2/6, Criterion 76/5N, CR; Predictor Set 2/6, Criterion 76/ON, CR; Predictor Set 2/6, Criterion 76/SW, CR; and Predictor Set 2/6, Criterion 77/5M, CR).

Each model, then, was cross-validated against three independent reconnaissance missions: Film 76, A/G 3; Film 77, A/G 3; and Film 76, Spot Wobble. (Criterion 43/ON is not truly independent of 43/5N, nor is 76/ON independent of 76/5N.)

The validation of the sample model discussed in Phase I against Mission 76/Spot Wobble will be described:

$$Y' = 12959 + 10204 (P28) - 1151.7 (P30) - 1.4931 (P20) \quad (2)$$

Y' , the predicted ground range at acquisition for a given target, was computed by substituting into the equation the values of Predictors 28, 30, and 20 in Predictor Set 2/6. For Film 76, target number 9,

$$\begin{aligned} Y' &= 12959 + 10204 (.081) - 1151.7 (1.296) - 1.4931 (531) \\ &= 11500 \end{aligned} \quad (2a)$$

Y' was computed for the other eight targets in the same manner; then a regression analysis between Y' values and actual performance measures in mission 76/SW (Y_s) was performed. The Y -intercept (b), the slope of the regression line (m), and the Pearson product-moment correlation between Y' and Y (r) are computed. In this example, $b = 21,945$; $m = 4.8402$; $r = .78$.

The reader may find it disconcerting that the Y intercept nearly doubled from that in the original model and the slope is closer to five than to one. These phenomena are due to differences in means and variance of performance distributions of each film, caused by differences in filming conditions. (For example, the depression angle of Film 76 is 23° ; that of Film 43 is 45° .) Thus, the results suggest that different constants (m and b) are needed for different missions.

Each of the 60 models (5 Steps x 4 Predictor Sets x 3 IR definitions) were applied in this manner to each of five criteria.

Program III served this purpose.

Inputs: Program III

Predictor variable numbers

Criterion numbers

Regression coefficients

BMD data deck (values of predictor variables and criteria)

Outputs: For each step, predictor set, and IR definition:

Y' for each target

r, m, and b for each mission

Validity coefficients at each of five steps are presented in Tables 9 through 13. The first column shows multiple R obtained in Phase II model development. The second column is shrunken R, or the multiple correlation one would expect in cross-validation, and is given by the formula:

$$R_s = \sqrt{1 - [(1 - R^2) \times (N - 1) / (N - k - 1)]}$$

where R_s = shrunken multiple correlation

R = multiple correlation in column 1

N = number of targets in validation sample (=9)

k = number of predictors in regression equation (1, 2, 3, 4, or 5)

Phase III results were encouraging. An inspection of Tables 9 through 13 indicates that validity coefficients in some cases exceeded .90. The expected validity coefficient (R_s) was exceeded in 184 of 300 cross-validations, or in nearly two-thirds of the cases. These results alone showed that target acquisition performance can be predicted to some degree from microdensitometrically determined photometric and geometric characteristics of targets and their backgrounds.

Phase IV

Several questions still remained, such as: How many microdensitometric scans should be taken through a target? Which method of dealing with incorrect responses results in the most predictable criterion of target acquisition performance? How many predictors should be included in the prediction equation?

Table 9
Validity Coefficients for Step 1 Prediction Models

Criterion	Predictor set	43/5N	R _S	43/0N	76/5N	76/0N	76/SW	77/5N
CR	2/6	.61	.53	.61	.66	.76	.69	.73
	1/6	.62	.54	.40	.56	.70	.59	.75
	2/2	.64	.57	.59	.65	.52	.58	.68
	1/2	.62	.54	.56	.25	.50	.42	.50
CR + IR _{min}	2/6	.72	.67	.72	.86	.82	.75	.87
	1/6	.62	.54	.47	.73	.76	.65	.83
	2/2	.69	.63	.59	.68	.58	.80	.68
	1/2	.62	.54	.69	.81	.55	.69	.75
CR + IR ₀	2/6	.66	.60	.69	.85	.57	.66	.88
	1/6	.58	.49	.46	.71	.49	.57	.82
	2/2	.59	.50	.61	.83	.29	.69	.83
	1/2	.56	.46	.60	.80	.29	.65	.77

Table 10
Validity Coefficients for Step 2 Prediction Models

Criterion	Predictor set	43/5N	R _S	43/0N	76/5N	76/0N	76/SW	77/5N
CR	2/6	.81	.74	.69	.94	.76	.84	.58
	1/6	.73	.61	.56	.53	.69	.58	.73
	2/2	.68	.53	.66	.63	.59	.61	.69
	1/2	.80	.72	.78	.65	.56	.69	.81
CR + IR _{min}	2/6	.85	.79	.68	.83	.71	.70	.71
	1/6	.68	.53	.62	.83	.78	.74	.90
	2/2	.74	.63	.71	.71	.64	.83	.71
	1/2	.69	.55	.75	.83	.63	.74	.80
CR + IR ₀	2/6	.81	.74	.61	.67	.35	.31	.59
	1/6	.62	.42	.57	.78	.48	.64	.89
	2/2	.64	.46	.65	.33	.03	.17	.24
	1/2	.59	.36	.63	.81	.33	.69	.80

Table 11
Validity Coefficients for Step 3 Prediction Models

Criterion	Predictor set	43/5N	R _S	43/0N	76/5N	76/0N	76/SW	77/5N
CR	2/6	.82	.78	.75	.91	.66	.78	.41
	1/6	.78	.61	.60	.70	.79	.72	.72
	2/2	.75	.55	.75	.70	.58	.72	.83
	1/2	.90	.83	.90	.44	.23	.52	.48
CR + IR _{min}	2/6	.86	.76	.68	.80	.72	.67	.68
	1/6	.73	.50	.60	.85	.80	.77	.87
	2/2	.76	.57	.73	.90	.72	.96	.92
	1/2	.75	.55	.80	.83	.60	.83	.88
CR + IR ₀	2/6	.83	.71	.59	.68	.28	.44	.56
	1/6	.66	.31	.51	.76	.45	.56	.84
	2/2	.72	.48	.65	.53	.08	.43	.46
	1/2	.65	.28	.66	.73	.18	.78	.80

Table 12
Validity Coefficients for Step 4 Prediction Models

Criterion	Predictor set	43/5N	R _S	43/0N	76/5N	76/0N	76/SW	77/5N
CR	2/6	.89	.76	.77	.95	.69	.88	.61
	1/6	.86	.69	.70	.53	.44	.70	.53
	2/2	.77	.43	.77	.71	.63	.79	.85
	1/2	.93	.85	.90	.43	.23	.51	.53
CR + IR _{min}	2/6	.89	.76	.74	.83	.59	.81	.79
	1/6	.79	.50	.57	.73	.72	.65	.68
	2/2	.82	.59	.66	.75	.60	.84	.78
	1/2	.88	.74	.80	.47	.20	.60	.44
CR + IR ₀	2/6	.85	.67	.55	.56	.26	.43	.43
	1/6	.71	.09	.45	.63	.40	.35	.67
	2/2	.74	.31	.63	.71	.18	.63	.67
	1/2	.81	.56	.59	.37	.16	.54	.31

Table 13

Validity Coefficients for Step 5 Prediction Models

Criterion	Predictor set	43/5N	R_s	43/0N	76/5N	76/0N	76/SW	77/5N
CR	2/6	.91	.78	.81	.91	.70	.81	.70
	1/6	.94	.86	.79	.26	.12	.44	.32
	2/2	.82	.48	.82	.71	.52	.74	.61
	1/2	.96	.91	.90	.41	.21	.50	.54
CR + IR_{\min}	2/6	.89	.73	.74	.81	.56	.79	.75
	1/6	.87	.67	.70	.82	.78	.65	.81
	2/2	.83	.55	.68	.88	.71	.95	.91
	1/2	.93	.83	.73	.39	.13	.53	.37
CR + IR_0	2/6	.89	.73	.59	.43	.12	.37	.27
	1/6	.82	.51	.57	.78	.52	.48	.84
	2/2	.81	.48	.57	-.10	.11	-.24	-.24
	1/2	.88	.70	.46	.29	-.21	.50	.24

These kinds of questions suggested an analysis of variance of Phase III correlational coefficients. The differential effects of Predictor Set, Criterion (IR definition), and Step (number of predictors in the prediction equation) were of interest. Each model predicted target acquisition performance in each of three independent reconnaissance missions (Film 76, A/G 3; Film 77, A/G 3; and Film 76, Spot Wobble). These three missions represent random samples of the population of reconnaissance missions and were independent not only of each other, but also of the mission from which the models were generated.

As mentioned earlier, criteria 43/5N and 43/ON came from the same mission and were therefore not truly independent. Criteria 43/ON were thus not included in the analysis of variance. Criteria 76/5N and 76/ON were similarly related, so only one of these should be included in an analysis of variance.

The mean validity coefficient across all models for criteria 76/5N was .67 and for criteria 76/ON, .48. A t-test confirmed the significance of this difference ($t = 106.59$; $df = 118$; $p < .001$). Since all other conditions were equal, this difference is due to the increase in reliability of the criterion when the number of trials on which it is based increases. Criteria 76/ON were omitted from the analysis of variance.

We have, then, a four-way factorial design: 3 Missions (76, A/G 3; 77, A/G 3; and 76, Spot Wobble) x 3 Criteria (CR, CR + IR_{min}, CR + IR₀) x 4 Predictor Sets (2/6, 1/6, 2/2, 1/2) x 5 Steps, where Mission is the random independent variable and validity coefficients the dependent variable. Predictor Sets, Criteria, and Steps are considered fixed effect variables in this model. Table 14 summarizes the results of the analysis of variance.

For the Criterion effect, mean validity coefficients are as follows: CR, .64; CR + IR_{min}, .76; CR + IR₀, .56.

The best prediction is obtained when the ground range of an undetected target is defined as the minimum available range. A Neuman-Keuls test showed all differences significant at the .05 level of confidence.

There were no significant differences among predictor sets, although there was a slight decrease in prediction as the prediction base shrank:

2 frames, 6 scans/frame:	.69
1 frame, 6 scans/frame:	.68
2 frames, 2 scans/frame:	.64
1 frame, 2 scans/frame:	.59

Table 14
Analysis of Variance of Validity Coefficients

Source of variance	df	MS	F
Mission (M)	2	.0229	
Criterion (C)	2	.5981	17.04*
Predictor Set (P)	3	.0893	1.82
Step (S)	4	.1850	12.85**
C x P	6	.1978	9.46***
C x S	8	.1049	47.68***
P x S	12	.0698	15.51***
C x P x S	24	.0582	16.17***
M x C	4	.0351	
M x P	6	.0490	
M x S	8	.0144	
M x C x P	12	.0209	
M x C x S	16	.0022	
M x P x S	24	.0045	
M x C x P x S	48	.0036	
Total	179		

*p < .025.

**p < .005.

***p < .0001.

The Step effect was significant at the .05 level:

Step 1: .70
Step 2: .68
Step 3: .71
Step 4: .63
Step 5: .53

Only the difference between Step 1 and Step 3 was insignificant at the .05 level of confidence. Thus, models including three predictors yielded the highest validity coefficients, but a single predictor was equally effective.

All interactions were highly significant. These effects are seen in Figures 9 through 14. Figures 9 and 10 suggest that the interactions between Criterion and Predictor Set, and between Criterion and Step, were due to Criterion CR + IR₀. The pronounced interaction between Predictor

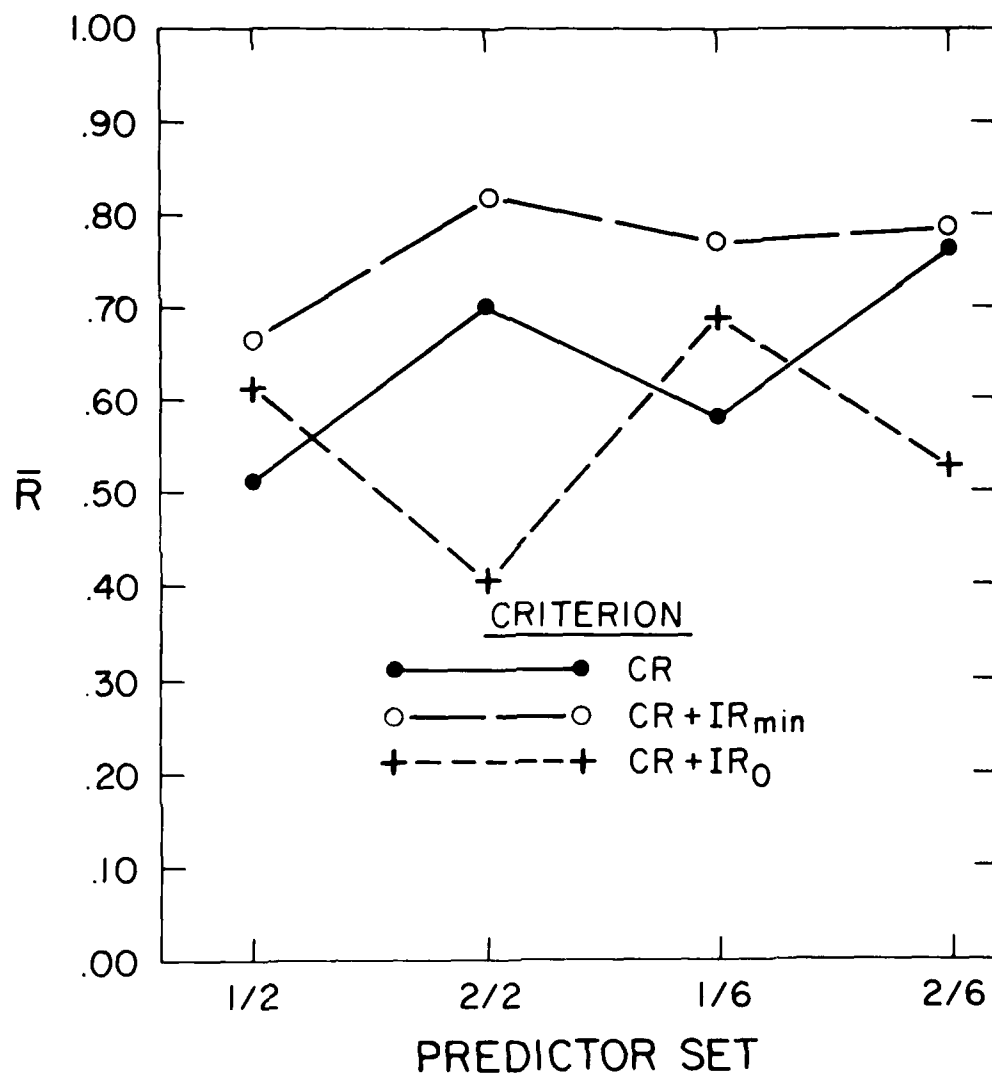


Figure 9. Criterion x Predictor Set interaction.

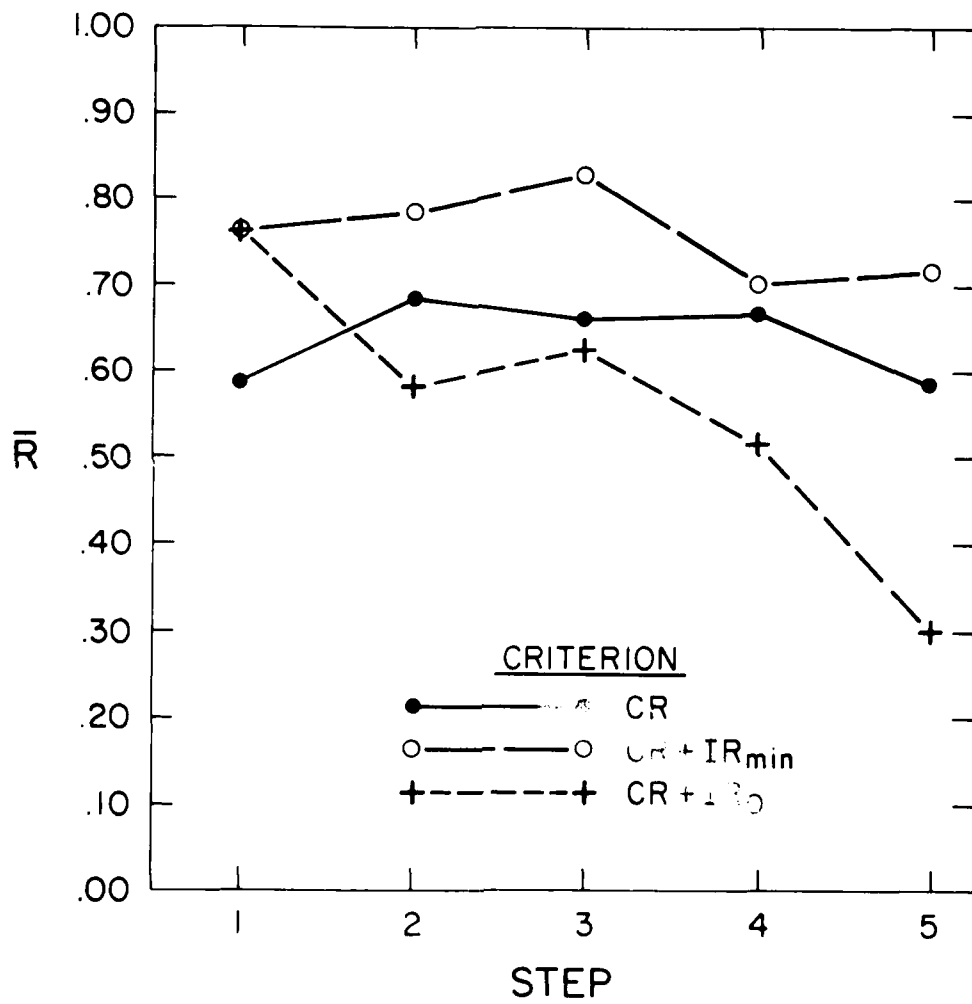


Figure 10. Criterion x Step interaction.

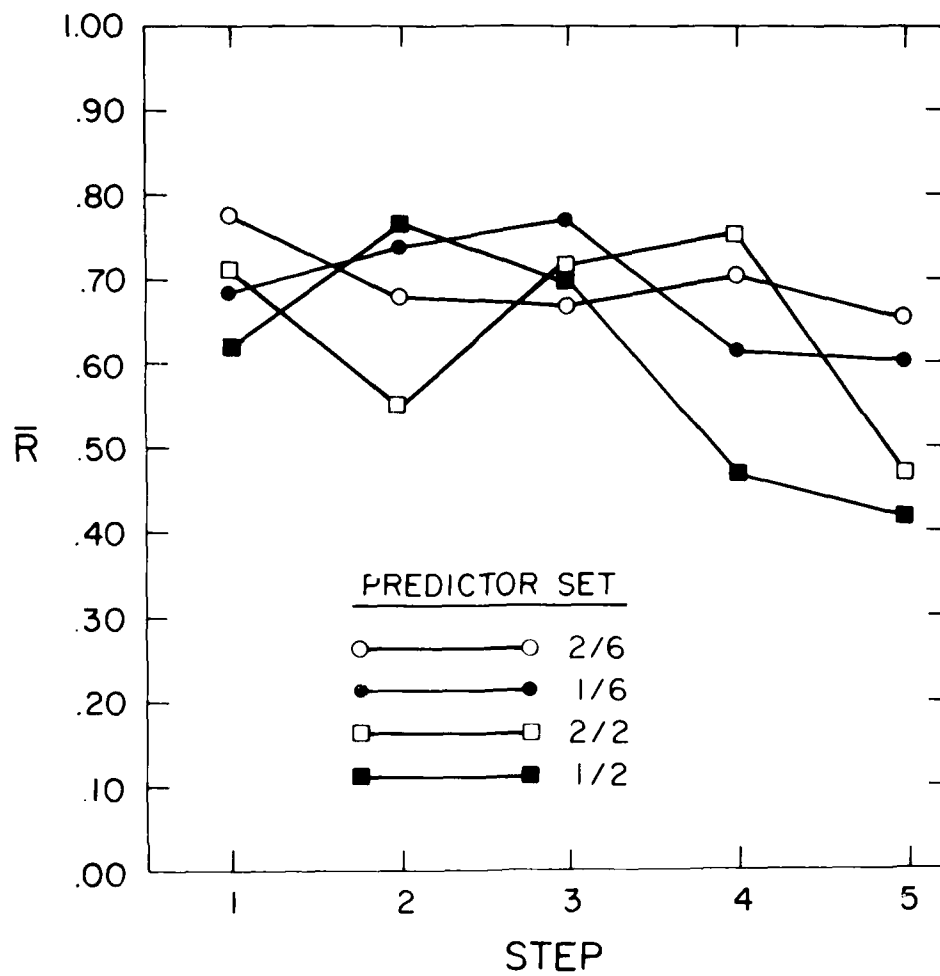


Figure 11. Predictor Set x Step interaction.

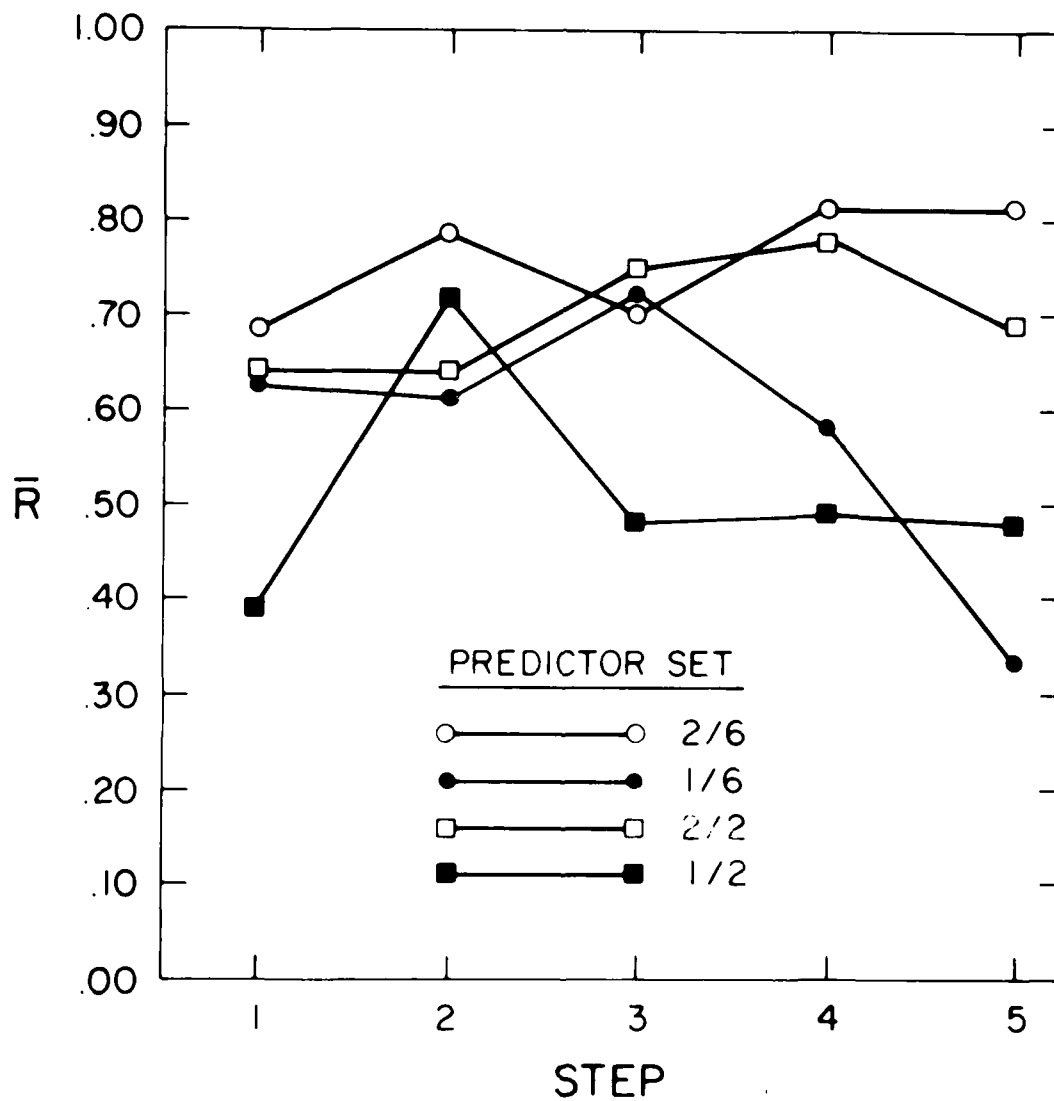


Figure 12. Criterion x Predictor Set x Step interaction: Criterion CR.

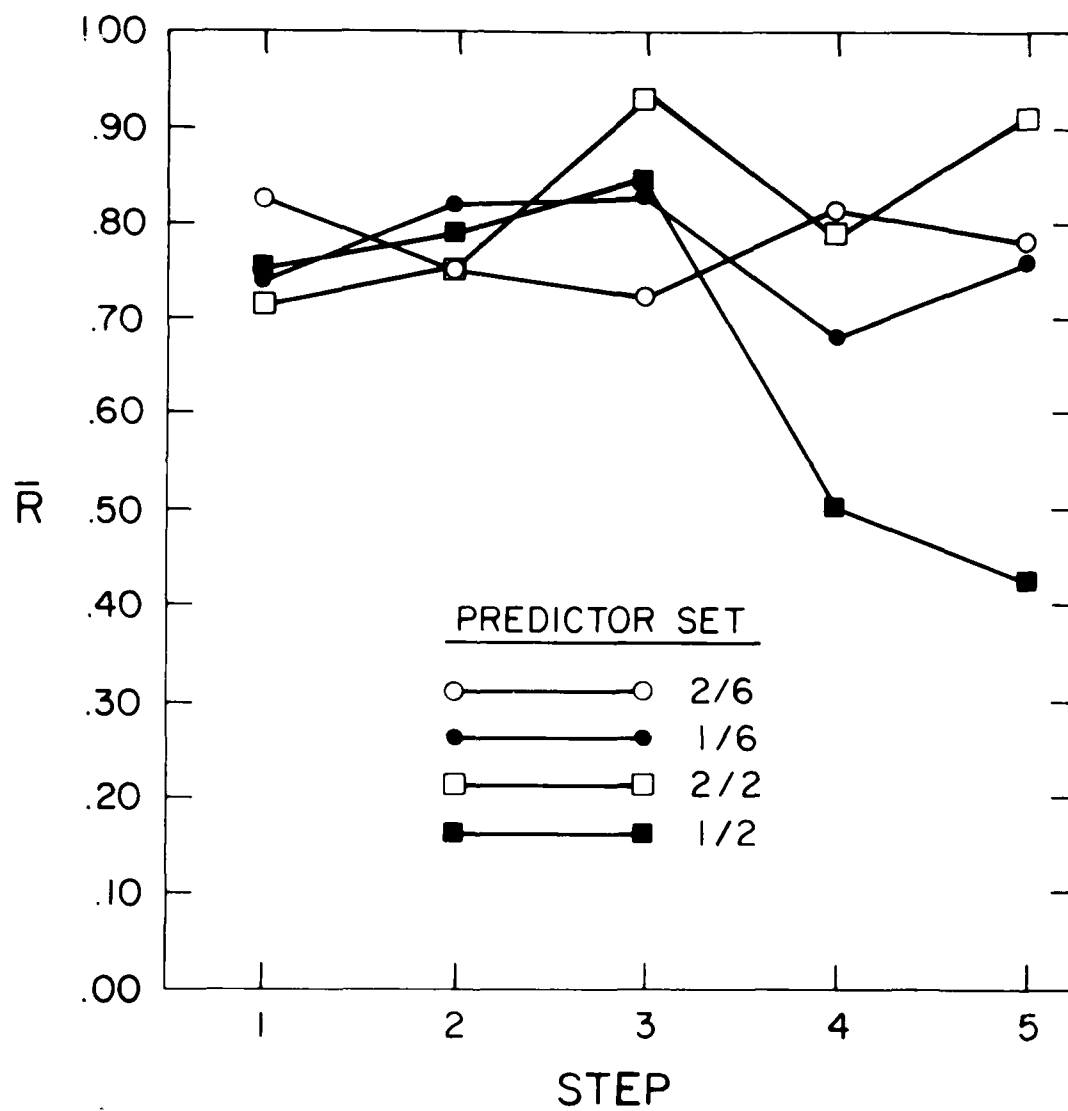


Figure 13. Criterion x Predictor Set x Step
interaction: Criterion $CR + IR_{min}$.

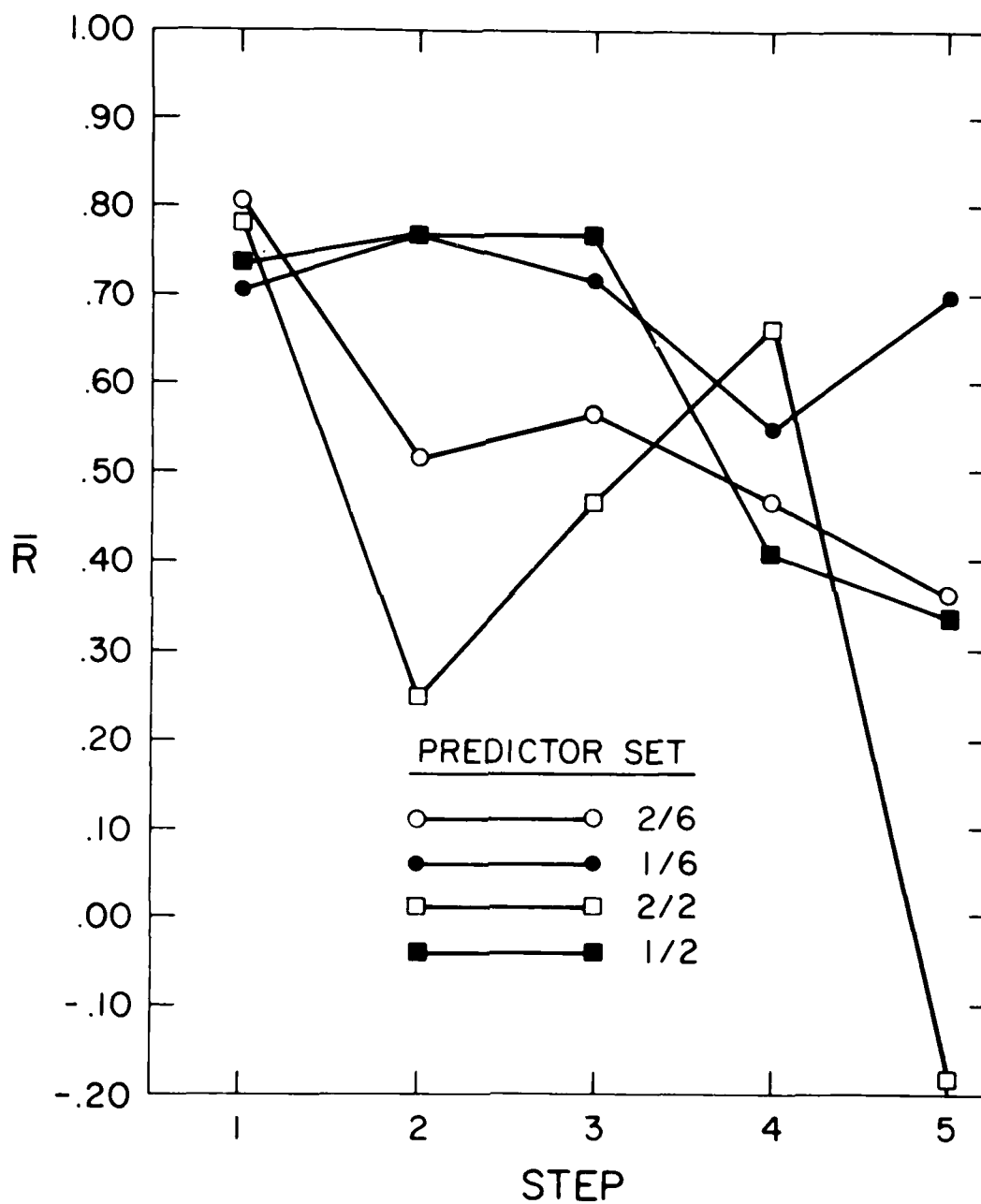


Figure 14. Criterion x Predictor Set x Step interaction: Criterion CR + IR₀.

Set and Step at CR + IR₀ (Figure 14) may have also caused the Predictor Set x Step and three-way interactions.

Therefore, the mean squares and F ratios of all fixed effects were recomputed for Criteria CR and CR + IR_{min} only. Error terms for these simple effects tests were retained from the original analysis of variance. Results are shown in Table 15.

Table 15
Analysis of Variance of Validity Coefficients When
Criterion CR + IR₀ Is Excluded

Source of variance	df	MS	F
Mission (M)	2	.0029	
Criterion (C)	1	.4260	12.14*
Predictor Set (P)	3	.1451	2.96
Step (S)	4	.0260	1.81
C x P	3	.1137	3.92**
C x S	4	.0076	3.45**
P x S	12	.0654	14.53***
C x P x S	12	.0136	3.78***
M x C	4	.0351	
M x P	6	.0490	
M x S	8	.0144	
M x C x P	12	.0209	
M x C x S	16	.0022	
M x P x S	24	.0045	
M x C x P x S	48	.0036	

*p < .05.

**p < .005.

***p < .0001.

The significant (p < .05) Criterion effect indicates that Criterion CR + IR_{min} is significantly more predictable than Criterion CR.

The Predictor Set effect was not significant, but the change in trend when Criterion CR + IR₀ was removed is interesting:

2/6: .77
1/6: .67
2/2: .76
1/2: .58

With the inclusion of Criterion $CR + IR_0$, R increased systematically with an increased number of scans. It can now be seen that more reliable prediction is obtained from a total of four microdensitometric scans of two frames than from six scans of a single frame, and that if two frames are scanned, two orthogonal scans per frame are virtually as beneficial as six!

The exclusion of Criterion $CR + IR_0$ eliminated no interactions. The recomputed Predictor Set x Step interaction is shown in Figure 15.

In summary, Phase IV analyses showed that the most predictable criterion of target acquisition performance is $CR + IR_{min}$. A linear combination of three predictor variables yields the best predictive validity. Predictor variables computed from microdensitometric scans of two film frames give the best results; whether two or six scans are made of each frame is of little consequence.

DISCUSSION

Phase IV Results

Results show that, of the three criteria of target acquisition performance studied, Criterion $CR + IR_{min}$ is most predictable. Defining the ground range at acquisition for an undetected target as the minimum available range accounts for the information contained in the target's nonacquisition without inflating the importance of incorrect response trials.

This criterion is not only predictable; it is also meaningful. If the predicted ground range at acquisition is large, a high probability of target acquisition can be anticipated. Similarly, if a model predicts that a target will first be detected when it is nearly out of the bottom of the field of view, it is often the case that the target will not be detected at all. Models predicting Criterion CR, on the other hand, make the tenuous assumption that a given target will be detected and include no penalty for nondetection. If Criterion $CR + IR_0$ is predicted we may find that, on the average, target A will be "detected" when it is 100 ft out of the field of view, but target B will not be "seen" until it is 1,000 ft out of the field of view. This kind of "information" has no practical advantage over that obtained from Criterion $CR + IR_{min}$.

The Predictor Set effect was not statistically significant. However, there is evidence that predictor variables derived from microdensitometric scans of multiple film frames more reliably predict target acquisition performance than predictors derived from a single frame. Criterion $CR + IR_{min}$ correlated most highly with predictors derived from two orthogonal scans of each of two frames containing the target; R across steps and missions was .82.

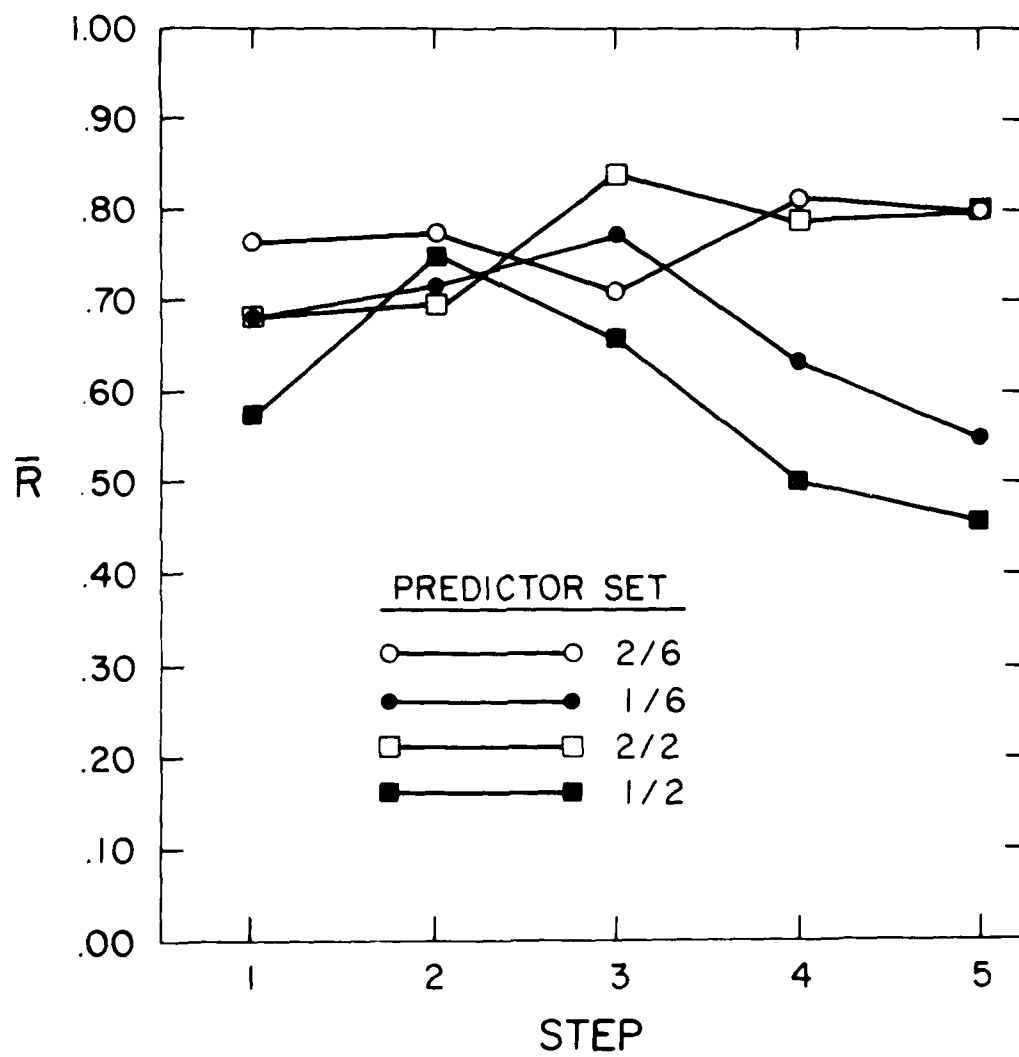


Figure 15. Predictor Set x Step interaction when Criterion CR + IR₀ is excluded.

If a target is very small with respect to the background, all parallel scans through that target are likely to contain highly redundant background information. If the target is photometrically and geometrically symmetric (as man-made objects tend to be), the target information contained in those scans is also redundant.

On the other hand, if we pass a scan through the target's center in each of two frames, overlapping but not identical portions of the background are sampled. The photometric and geometric characteristics of the target and redundant background portions also change somewhat with distance. These two scans, then, are more independent than two parallel scans of a single frame, and together constitute a larger and more representative sample of the scene's photometry and geometry.

In multiple linear stepwise regression, R increases with the addition of each variable into the regression equation. As the number of predictors in solution approaches the number of targets, R approaches 1.00. However, as each predictor is added, the regression equation is more influenced by the uniqueness of that particular sample of targets. When Criterion $CR + IR_0$ was excluded it was found in cross-validation that R increases with the addition of up to three predictors, then begins to decline.

With more reliable criteria and predictor sets, more predictor variables can be meaningfully included in the regression equation. For Criterion $CR + IR_0$, a single predictor gave the highest predictive validity and R declined as more predictors were added. But for Criteria CR and $CR + IR_{min}$, R remained relatively high when up to five predictors were included in the predictive model (Figure 10). Similarly, for Predictor Sets 1/6 and 1/2, R peaked at Step 2, but for Predictor Sets 2/2 and 2/6, R continued to increase through step 4 (Figure 11).

It is reasonable that "good" criteria should combine well with "good" predictor sets. But it also seems that "poor" criteria combine best with "poor" predictor sets. That is, for Criteria CR and $CR + IR_{min}$, the best predictor sets are 2/6 and 2/2. But for Criterion $CR + IR_0$, Predictor Sets 1/6 and 1/2 result in the highest validity (Figure 9).

This interaction also affects the number of predictor variables a model can withstand in cross-validation. Compare, for example, the validities of several Step 5 Models (Figures 13 and 14). The combination of Criterion $CR + IR_{min}$ and Predictor Set 2/2 gives a Step 5 validity of .91. When the same criterion is combined with Predictor Set 1/2, R equals .43. The combination of "poor" Criterion $CR + IR_0$ and "good" Predictor Set 2/2 gives a small negative correlation of -.19. But when that same criterion is combined with the generally "poor" Predictor Set 1/6, R is .70.

Phase III Results

Results show the best prediction of dynamic target acquisition performance is obtained when:

$$\begin{aligned} {}^5 \text{Predicted performance} = & .4176 \text{ (Mean tgt Mod)} - .2671 \text{ (Rev bgd)} \\ & + .2976 \text{ (Rev 25)} \end{aligned} \quad (3)$$

In one cross-validation, this equation accounted for 92% of the criterion variance ($R = .96$). Across three validations the average validity coefficient was .93. (In a later portion of the Discussion section, the importance of each variable in this prediction equation will be described and related to other research.)

In only one previous attempt at predicting target acquisition performance were results nearly so encouraging. Rhodes' (1964) best prediction model accounted for 70% of the variance in a validation sample ($R = .84$) and included 14 predictor variables. The practical value of his model is, however, somewhat limited. First, static target acquisition performance was predicted. In static image target detection tasks, search time is not normally the determining factor of success, as it is in dynamic situations. Secondly, Rhodes' prediction equation relies primarily on predictor variables determined from psychophysical judgments of a large number of subjects, making its application impractical in a field setting.

If a technique were developed for identifying the target area with a flying spot scanner, Corbett et al.'s (1964) five predictor variables could be calculated automatically in the field. The best model developed in that study, however, showed a predictive validity of only .28, not significantly different from zero. Again, static target acquisition was the criterion.

Phase II Results

As Zaitzeff's (1971) results were not cross-validated, they are most appropriately compared to Phase II results of the present study. Although Zaitzeff's model was based on an N of 100, 10 different frames of each of 10 targets comprised the sample. Thus, his N really only represents 10 independent targets, which is not much different from the 9 used in this study. With 7 predictors in solution, Zaitzeff's R was .89.

⁵Regression coefficients are expressed as Beta weights. Criterion $CR + IR_{\min}$, Predictor Set 2/2, Step 3.

If Phase II results of the present study are considered in isolation, the best model⁶ contained five predictors and R was .96. In cross-validation, however, this model was a relatively poor predictor of performance; over three replications the mean validity coefficient was .48. Thus, high multiple correlations between predictors and the criterion from a single sample of targets should be viewed with considerable caution, especially if N is small.

Phase I Results

In Phase I, 17 target and background characteristics extracted from the information contained in microdensitometric scans were found to be consistently linearly related to target acquisition performance over 48 replications. Several of the other original 36 predictor variables showed a linear relationship to performance but did not pass the rather stringent test for inclusion in further analyses. These are: Target standard deviation (P7), Overall standard deviation (P8), Maximum target modulation, 25% background (P32), Maximum target modulation (P31), and Ratio of target to background standard deviation (P33) (see Table 4). Thus, at least 22 of the 36 predictors show promise as components of linear models of target acquisition performance; others may be useful in nonlinear models.

In no previous study have microdensitometrically determined photometric and geometric scene characteristics been highly related to target acquisition performance, either static or dynamic. Perhaps previous researchers chose less relevant parameters for investigation, or perhaps previous scanning procedures resulted in unreliable photometric measurement.

Zaitzeff found psychophysical judgments to hold more promise than photometric variables as predictors of dynamic target acquisition. This could have been a result of his use of color, rather than black-and-white, imagery. Microdensitometers, unlike human judges, respond only to differences in (photopic) luminance; the dimension of hue is left untapped. Further, Zaitzeff's photometric variables were derived from a single horizontal scan passed through each target scene; such a scan constitutes a very small sample of the scene's photometry.

Nygaard et al. (1964) and Corbett et al. (1964), on the other hand, obtained a very large sample of the scene photometry through the use of a flying spot scanner. This apparatus, however, does not lend itself to precise isolation of target samples from background samples. Nygaard et al. made no attempt to distinguish between the two; their photometric variables were total scene characteristics. The rather tedious target isolation method used by Corbett et al. permitted only a gross distinction between target and background samples, which may

⁶Criterion CR, Predictor Set 1/2.

have resulted in unreliable predictors. The use of side-looking airborne radar imagery instead of aerial reconnaissance motion pictures may have also influenced the generally discouraging results of these two studies.

Table 16 lists the variables which previous researchers have found most reliably related to target acquisition performance. The 17 most important variables isolated in Phase I of the present study are listed in Table 17, grouped according to the scene characteristics each variable presumably measures. The number of times each predictor was included in each step of the Phase II regression equations is listed, as well as the mean correlation to criteria taken from Table 4. This information indicates to some degree the relative importance of the 17 predictors, as do the Beta weights shown in Tables 9 through 13.

Some of these predictors are highly related to important predictors in previous research with real-world imagery. Others are meaningful in the light of basic research in form perception.

Target Luminance Measures. Integrated target luminance is an index of the total amount of light reflected from the target, or the product of mean target luminance and target size. According to Ricco's Law (Graham, 1966, cited in Kling & Riggs, 1972), the absolute threshold for vision is a critical light-energy (E_c), representing the product of luminance (L) and area (A), or $E_c = KAL$, where K is a constant. This linear relationship between integrated target luminance and luminance threshold normally describes target detection performance best for targets subtending less than 10 minutes of arc, but spatial summation contributes to the visual threshold of targets as large as 10 degrees in diameter (Graham, 1934). Certainly, the dynamic recognition of a complex target in a complex background requires more than suprathreshold target luminance. However, the correlation between the criterion measures and integrated target luminance is about .50, indicating that Ricco's Law explained approximately 25% of the variance in dynamic target acquisition performance.

As virtually all basic research in the perception of form has dealt with targets of uniform luminance, the parameter maximum target luminance has not been previously investigated. However, this predictor may be interpreted in the light of modulation transfer functions. Most targets subtended approximately one-half degree of arc at the time of recognition and consisted of two or three light elements in either dimension. Using the three POL tanks, for instance, at an angular subtense of one-half degree, if a Fourier analysis were performed on a microdensitometric trace through these three POL tanks, a sinusoidal component would emerge with an amplitude proportional to maximum target luminance and a frequency of six cycles/degree. At approximately six cycles/degree the visual system spatial sensitivity is maximal (Cornsweet, 1970), and the apparent contrast between the light target detail and its background is increased in prominence relative to other spatial frequency information. As the target detail

Table 16

Most Important Variables in Previous Studies

Investigator and variable	Method of measurement
Nygaard et al. (1964)	
σ^2 Object Size	Photometric scan analysis
Mean Object Size	Photometric scan analysis
Total Count/Unit Area	Photometric scan analysis
Corbett et al. (1964)	
Target/Background Mean Transmissivity	Photometric scan analysis
Target/Background Mean Derivative	Photometric scan analysis
Rhodes (1964) (Dimensions isolated through factor analysis)	
Target Size	Psychophysical
Target Shape-pattern	Psychophysical
Target Isolation	Psychophysical
Zaitzeff (1971)	
Target Length	Direct measurement
Target Width	Direct measurement
Detail Contrast	Photometric scan analysis
Target Contrast	Photometric scan analysis
Element Count	Photometric scan analysis
Ambiguity	Psychophysical
Heterogeneity	Psychophysical

Table 17
Most Important Predictors in Present Study

Predictor	\bar{r} from Table 4	Number of times entered into Phase II models at Step				
		1	2	3	4	5
Target luminance						
10 XY tgt	.57					
11 Max Y tgt	.31				1	
Target size and geometry						
13 Tgt Size	.59		2			5
14 Tgt L	.55				1	2
15 Tgt W	.60	4				
24 L/W	.34				1	1
21 Rev 25	.30		1	4	2	
22 Rev tgt	.54			1	2	2
Background heterogeneity						
20 Rev bgd	-.46	1	5	1		
Target/background contrast						
25 Mean tgt Cont	.49					2
26 Mean tgt Cont, 25	.61	3				
27 Mean tgt Mod	.52	1			1	1
28 Mean tgt Mod, 25	.60	3		1	2	
29 Max tgt Cont	.25			1	1	
30 Max tgt Cont, 25	.26		4	3		1
35 Int tgt Cont	-.59					2
36 Int tgt Mod	-.61			1		

at this spatial frequency increases in amplitude, the distance at which the target is detected should increase (Snyder et al., 1974).

Target Size and Geometry. It has been amply demonstrated that large things are more detectable than small things. Green, McGill, and Jenkins (1953) found this true of numbers and Rhodes (1964) of real objects, just to name a couple.

In both Zaitzeff's (1971) study and the present one, target length and width were reliable predictors. One might expect target width to be more relevant than length in dynamic air-to-ground target acquisition since a target's apparent length is necessarily small at long range due to the viewing geometry. This may, in fact, be the case. Although the mean predictive power of target width was only slightly greater than that of target length, the difference may normally be more pronounced. The two variables were measured in equivalent units, but the variance of width across targets was less than one-seventh of the variance of length. In spite of this relative restriction in range, target width was a slightly better predictor.

The relative variance of target length and target width suggest an artifactual explanation of the positive relationship between vertical aspect ratio and performance. A negative correlation was predicted. However, since target width was relatively constant for the sample of targets, vertical aspect ratio was essentially a transformed measure of target length. Consistent with this explanation, the mean correlational coefficient of vertical aspect ratio was considerably less than that of target length.

It is not immediately obvious that the number of reversals in the target and 25% background are indirect measures of target size. However, neither of these metrics was corrected for target size and, thus, the number of reversals is largely a function of the number of samples of the trace contained in each film segment. Both variables correlated highly with the other measures of target size but not with Rev bgd, lending further support to this argument.

In spite of the size component contained in target reversals there is evidence that target heterogeneity facilitates target detection. The mean correlational coefficient for Rev tgt was greater than that for Rev 25; if only size is tapped by Rev tgt, both predictors should be equally powerful. Further, σ tgt was positively related to performance in 46 of 48 cases.

Background Heterogeneity. The number of reversals in the background was the best measure of background heterogeneity. This variable is essentially equivalent to Nygaard et al.'s (1964) Total Object Count and Zaitzeff's (1971) Element Count. Background heterogeneity contributes to visual competition, which has also been produced in artificial target detection tasks by imbedding a geometric target in a field of similar geometric shapes. It has been repeatedly demonstrated

that search time increases with the number of nontarget stimuli in the display (i.e., Bonnet and Snyder, 1974; Green et al., 1953).

Target/Background Contrast. Six measures of target-to-background contrast were reliable predictors of performance. This result is consistent with classical visual psychophysics (e.g., Graham, 1966), as well as with the results of Corbett et al. (1964) and Zaitzeff (1971).

Whether target-to-background contrast is computed in the traditional manner or as modulation seems to be of little significance. Measures comparing target luminance to the immediate surround are at least as good as those comparing the target to the entire background. Mean target luminance is more effectively compared to the background than is maximum or minimum target luminance.

Combinations of Measures. The best prediction equation identified in Phase IV included one measure of target size (P21), one of background heterogeneity (P20), and one of target-to-background contrast (P27). These three dimensions include most of the information required for reliable prediction of target acquisition performance.

The purpose of this research was to investigate the feasibility of meeting the following conditions necessary for field prediction of real-time air-to-ground target acquisition performance:

1. One knows what microdensitometric scans to make of available reconnaissance imagery.
2. One knows what measures to extract from these scans.
3. One knows how to combine these measures into an equation to predict mission success.

Conditions (1) and (2) can clearly be met. At least two orthogonal scans of at least two frames (distances) containing the target should be made. Future research may suggest that prediction can be further improved by scanning more than two frames. At least three of the 17 best predictors should be calculated. One predictor should be a measure of target size, one of background heterogeneity, and one of target/background contrast.

The results of the present study indicate that the third condition can be met. However, further research is required before a field commander can reliably predict the target acquisition performance for a given mission under any given combination of mission conditions.

Prediction equations were developed under one combination of mission conditions. The mission was flown in broad daylight, in clear weather, at an altitude of 10,000 ft. Ground imagery was viewed through a video display. The camera's field of view was 14.2° by 18.8° .

and its depression angle was 45° from horizontal. Groundspeed was 500 ft/sec.

Targets in the validation samples were viewed under similar circumstances; only the camera's depression angle and groundspeed were different. When prediction equations were applied to these targets, predicted target acquisition correlated highly with actual performance.

This does not mean that the predicted ground range was approximately equivalent to the actual ground range at acquisition. In many cases the predicted criterion range was out of the field of view and, in itself, meaningless. The field commander is not typically interested in the relative detectability of several targets (which the original prediction equation would not give him), but in the absolute ground range at which he can expect a given target to be recognized under given conditions.

Thus, he must know how the original prediction equation should be corrected for his mission conditions. In the present example, this involves nothing more than multiplying the criterion predicted from the original equation by a constant (m, as described in Results and Analyses) and adding a constant (b), where the values of the constants are functions of the depression angle and groundspeed.

Only further research can establish whether conditions other than groundspeed and camera depression angle can be varied without substantially reducing the correlation between predicted and actual performance. If correlations are high, and if the values of correcting constants m and b were available for a large number of combinations of viewing conditions, then one could predict performance on one mission from predictive models generated under different circumstances. In addition, one could also predict mission success on a foggy day from reconnaissance imagery filmed on a clear day.

In future studies of this type a larger number of targets should be included. The extent to which the relatively small samples used in the present study may have influenced the results is not known. Even though predictive models were cross-validated, it is possible that prediction may have been inflated by small samples. Future researchers may optimize their efforts from the finding that increasing the number of scans through a given frame is of little value and from the identification of a reasonable and predictable criterion of performance.

System Considerations. Finally, predictor variables may be appropriately derived from a transformation of the film transmission function which more closely represents the displayed luminance function seen by the observer. In the present study, photometric and geometric parameters of the scene were derived directly from film transmission data; it was implicitly assumed that perceived brightness (system output) is directly proportional to film transmission (system input).

We know, however, that this is not precisely the case. The aperture response of the TV system attenuates high spatial frequencies more than low spatial frequencies. That is, it has a typical modulation transfer function (Snyder et al., 1974). The human visual system further attenuates both low and high spatial frequencies. Thus, total system (TV plus human) attenuation is quantified by the modulation transfer function of the TV system and by the describing function of the visual system. In order to transform the transmission function into a perceived brightness function, a Fourier analysis can be performed on the transmission function. The Fourier line spectrum can then be multiplied, in turn, by the TV system's modulation transfer function and by the visual system's describing function. Fourier synthesis can then be performed, resulting in the brightness function perceived by the human observer. Predictor variables derived from this function would more accurately represent what the observer actually "sees," and may therefore result in more powerful prediction.

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APPENDIX

PREDICTOR AND CRITERION DATA BY TARGET AND PREDICTOR SET

The 36 predictor variables are given in the order listed in Table 2. Tabled data are those derived from the micro-densitometric scans as indicated in the text.

FILM 43 TARGET NUMBER 0

PREDICTOR NUMBER	2/6	PREDICTOR SFT 1/6	2/2	1/2
1	552.000	540.000	558.000	544.000
2	710.000	655.000	726.000	660.000
3	626.000	602.000	519.000	554.000
4	557.000	544.000	556.000	544.000
5	240.000	233.000	213.000	230.000
6	267.000	241.000	332.000	262.000
7	372.000	339.000	198.000	191.000
8	250.000	241.000	212.000	228.000
9	2423.000	2333.000	2486.000	2351.000
10	171.000	166.000	140.000	145.000
11	1535.000	1535.000	1259.000	1211.000
12	106.000	148.000	334.000	334.000
13	0.059	0.060	0.057	0.057
14	1327.000	1327.000	1197.000	1177.000
15	1729.000	1729.000	1594.000	1440.000
16	81.000	92.000	95.000	83.000
17	2.000	2.000	3.000	3.000
18	5.000	5.000	6.000	4.000
19	85.000	97.000	90.000	87.000
20	619.000	627.000	647.000	619.000
21	7.000	9.000	13.000	10.000
22	28.000	28.000	28.000	23.000
23	647.000	655.000	675.000	642.000
24	0.767	0.767	0.760	0.817
25	0.132	0.115	0.070	0.018
26	0.129	0.081	0.285	0.161
27	0.062	0.054	0.036	0.009
28	0.069	0.042	0.166	0.087
29	1.776	1.843	1.256	1.266
30	1.135	1.344	0.734	0.835
31	0.470	0.480	0.386	0.380
32	0.362	0.402	0.269	0.294
33	1.550	1.455	0.930	0.830
34	1.303	1.407	0.596	0.729
35	0.929	0.929	0.944	0.938
36	0.868	0.867	0.893	0.864

CRITERION	CR	CR + IR _{min}	CR + IR ₀
43/5N	12182.	12182.	12182.
43/0N	11800.	11800.	11800.

FILM 43 TARGET NUMBER 13

PREDICTOR NUMBER	PREDICTOR SET			
	2/6	1/6	2/2	1/2
1	451.000	491.000	432.000	456.000
2	451.000	489.000	416.000	425.000
3	515.000	559.000	468.000	464.000
4	454.000	493.000	433.000	455.000
5	127.000	137.000	123.000	142.000
6	112.000	119.000	80.000	51.000
7	169.000	173.000	151.000	142.000
8	130.000	139.000	124.000	142.000
9	1980.000	2155.000	1924.000	2066.000
10	93.000	92.000	86.000	83.000
11	1160.000	941.000	975.000	922.000
12	141.000	141.000	164.000	227.000
13	0.039	0.036	0.040	0.038
14	699.000	679.000	699.000	661.000
15	1387.000	1120.000	1205.000	1120.000
16	104.000	96.000	99.000	101.000
17	2.000	2.000	2.000	2.000
18	11.000	16.000	3.000	2.000
19	115.000	112.000	102.000	103.000
20	625.000	650.000	645.000	703.000
21	8.000	9.000	7.000	6.000
22	17.000	15.000	20.000	20.000
23	642.000	666.000	665.000	723.000
24	0.524	0.598	0.580	0.590
25	0.142	0.138	0.083	0.018
26	0.142	0.143	0.125	0.092
27	0.066	0.065	0.040	0.009
28	0.066	0.143	0.059	0.044
29	1.572	0.916	1.257	1.022
30	1.572	0.924	1.344	1.169
31	0.440	0.341	0.386	0.338
32	0.440	0.316	0.402	0.369
33	1.331	1.263	1.228	1.000
34	1.509	1.454	1.888	2.784
35	0.953	0.957	0.955	0.960
36	0.910	0.918	0.914	0.923

CRITERION	CR	CR + IR _{min}	CR + IR ₀
43/5N	11045.	10965.	10249.
43/0N	10231.	9872.	7724.

FILM 43 TARGET NUMBER 17

PREDICTOR NUMBER	PREDICTOR SET			
	2/6	1/6	2/2	1/2
1	644.000	649.000	646.000	651.000
2	743.000	735.000	801.000	782.000
3	775.000	851.000	774.000	859.000
4	648.000	654.000	650.000	658.000
5	151.000	127.000	149.000	120.000
6	145.000	153.000	108.000	120.000
7	227.000	238.000	208.000	218.000
8	155.000	135.000	153.000	130.000
9	2930.000	2926.000	2900.000	2883.000
10	99.000	107.000	117.000	123.000
11	1459.000	1459.000	1459.000	1459.000
12	103.000	265.000	245.000	310.000
13	0.027	0.027	0.033	0.031
14	1088.000	1089.000	999.000	795.000
15	761.000	663.000	635.000	635.000
16	78.000	89.000	78.000	95.000
17	1.000	1.000	1.000	1.000
18	3.000	1.000	3.000	1.000
19	80.000	91.000	82.000	96.000
20	729.000	739.000	732.000	768.000
21	6.000	7.000	5.000	2.000
22	13.000	13.000	18.000	17.000
23	742.000	741.000	749.000	785.000
24	1.430	1.641	1.573	1.252
25	0.203	0.311	0.198	0.320
26	0.043	0.158	0.034	0.098
27	0.092	0.135	0.030	0.138
28	0.021	0.073	0.017	0.047
29	1.266	1.248	1.259	1.241
30	0.964	0.985	0.821	0.866
31	0.388	0.384	0.386	0.383
32	0.325	0.330	0.291	0.302
33	1.503	1.874	1.306	1.817
34	1.566	1.556	1.926	1.817
35	0.966	0.963	0.960	0.957
36	0.935	0.929	0.922	0.918

CRITERION	CR	CR + IR _{min}	CR + IR ₀
43/5N	12111.	12111.	12111.
43/0N	11465.	10975.	9973.

FILM 43 TARGET NUMBER 21

PREDICTOR NUMBER	PREDICTOR SET			
	2/6	1/6	2/2	1/2
1	651.000	665.000	669.000	671.000
2	827.000	809.000	841.000	817.000
3	1184.000	1201.000	1024.000	990.000
4	687.000	697.000	694.000	691.000
5	179.000	182.000	173.000	176.000
6	144.000	82.000	68.000	66.000
7	486.000	486.000	417.000	416.000
8	253.000	249.000	220.000	214.000
9	2868.000	2935.000	2969.000	2980.000
10	379.000	341.000	346.000	296.000
11	1842.000	1842.000	1842.000	1842.000
12	193.000	368.000	334.000	334.000
13	0.068	0.060	0.071	0.063
14	2197.000	1542.000	1948.000	1542.000
15	1182.000	1450.000	1821.000	1450.000
16	67.000	66.000	70.000	75.000
17	1.000	1.000	1.000	1.000
18	7.000	7.000	5.000	6.000
19	74.000	73.000	75.000	81.000
20	679.000	683.000	698.000	700.000
21	18.000	20.000	18.000	18.000
22	59.000	49.000	52.000	42.000
23	738.000	731.000	750.000	742.000
24	1.206	1.603	1.077	1.063
25	0.819	0.806	0.531	0.571
26	0.432	0.485	0.218	0.212
27	0.290	0.287	0.210	0.192
28	0.178	0.155	0.093	0.096
29	1.829	1.770	1.753	1.745
30	1.227	1.277	1.190	1.255
31	0.474	0.469	0.467	0.466
32	0.387	0.390	0.373	0.385
33	2.715	2.670	2.410	2.364
34	3.375	5.927	6.132	6.303
35	0.868	0.884	0.883	0.910
36	0.767	0.702	0.791	0.828

CRITERION CR CR + IR_{min} CR + IR₀

43/5M	12319.	12183.	12319.
43/ON	12183.	12319.	12193.

FILM 43 TARGET NUMBER 22

PREDICTOR NUMBER	PREDICTOR SET			
	2/6	1/6	2/2	1/2
1	747.000	729.000	752.000	731.000
2	1117.000	1112.000	1033.000	971.000
3	1248.000	1233.000	1164.000	1131.000
4	758.000	739.000	761.000	740.000
5	292.000	275.000	285.000	266.000
6	177.000	210.000	121.000	90.000
7	182.000	199.000	189.000	210.000
8	299.000	283.000	290.000	272.000
9	3308.000	3186.000	3231.000	3165.000
10	125.000	115.000	112.000	113.000
11	1371.000	1371.000	1371.000	1371.000
12	714.000	714.000	714.000	714.000
13	0.022	0.021	0.021	0.023
14	1036.000	409.000	457.000	409.000
15	593.000	593.000	593.000	593.000
16	78.000	45.000	79.000	40.000
17	3.000	2.000	2.000	1.000
18	1.000	1.000	2.000	2.000
19	79.000	46.000	81.000	42.000
20	699.000	563.000	688.000	567.000
21	15.000	11.000	14.000	12.000
22	7.000	6.000	9.000	5.000
23	697.000	569.000	697.000	572.000
24	1.747	0.690	0.771	0.690
25	0.671	0.691	0.548	0.547
26	0.117	0.257	0.127	0.165
27	0.251	0.109	0.215	0.215
28	0.055	0.052	0.060	0.076
29	0.835	0.981	0.823	0.876
30	0.227	0.233	0.327	0.412
31	0.295	0.306	0.292	0.304
32	0.012	0.104	0.141	0.171
33	0.623	0.724	0.663	0.789
34	0.028	0.948	1.562	2.333
35	0.962	0.964	0.966	0.964
36	0.927	0.930	0.934	0.931

CRITERION	CR	CR + IR _{min}	CR + IR ₀
43/5N	12421.	11811.	11091.
43/0N	12568.	12446.	12302.

FILM 43 TARGET NUMBER 26

PREDICTOR NUMBER	2/6	PREDICTOR SET 1/6	2/2	1/2
1	545.000	469.000	522.000	454.000
2	650.000	529.000	524.000	456.000
3	1092.000	848.000	1146.000	874.000
4	719.000	575.000	810.000	6645.000
5	231.000	170.000	180.000	141.000
6	372.000	283.000	238.000	194.000
7	515.000	434.000	516.000	383.000
8	431.000	320.000	487.000	349.000
9	2017.000	1795.000	1521.000	1287.000
10	1895.000	1258.000	2873.000	2066.000
11	1906.000	1700.000	1976.000	1623.000
12	178.000	223.000	178.000	481.000
13	0.319	0.279	462.000	0.455
14	19716.000	18785.000	19716.000	18785.000
15	10972.000	8614.000	6806.000	4853.000
16	6.000	5.000	5.000	4.000
17	2.000	2.000	2.000	1.000
18	8.000	3.000	7.000	3.000
19	14.000	9.000	12.000	7.000
20	117.000	93.000	107.000	69.000
21	22.000	19.000	29.000	23.000
22	65.000	38.000	73.000	62.000
23	182.000	131.000	180.000	131.000
24	1.797	2.181	2.897	3.871
25	1.004	0.808	1.195	0.925
26	0.680	0.603	1.107	0.917
27	0.334	0.288	0.374	0.316
28	0.254	0.232	0.372	0.314
29	2.497	2.625	2.651	2.575
30	1.932	2.214	2.637	2.550
31	0.555	0.568	0.570	0.563
32	0.491	0.525	0.569	0.561
33	2.229	2.553	2.867	2.711
34	1.384	1.534	2.168	1.971
35	0.060	0.299	0.899	0.299
36	0.031	0.176	0.308	0.176

CRITERION	CR	CR + IR _{min}	CR + IR _{max}
43/5N	12946.	12946.	12946.
43/6N	13389.	13389.	13389.

FILM 43 TARGET NUMBER 32

PREDICTOR NUMBER	2/6	PREDICTOR SET 1/6	2/2	1/2
1	747.000	728.000	755.000	727.000
2	835.000	829.000	843.000	829.000
3	563.000	522.000	448.000	399.000
4	707.000	685.000	687.000	657.000
5	216.000	230.000	210.000	211.000
6	162.000	174.000	141.000	124.000
7	250.000	219.000	89.000	95.000
8	236.000	243.000	229.000	235.000
9	2706.000	2646.000	2720.000	2614.000
10	574.000	509.000	460.000	393.000
11	1782.000	1371.000	995.000	985.000
12	211.000	211.000	236.000	236.000
13	0.220	0.211	0.222	0.215
14	4849.000	4185.000	4849.000	4185.000
15	5873.000	5720.000	5873.000	5674.000
16	20.000	30.000	21.000	33.000
17	3.000	3.000	2.000	2.000
18	7.000	10.000	2.000	3.000
19	27.000	40.000	24.000	36.000
20	359.000	548.000	370.000	558.000
21	40.000	66.000	38.000	60.000
22	85.000	134.000	82.000	134.000
23	438.000	682.000	452.000	692.000
24	0.826	0.732	0.826	0.738
25	0.246	0.283	0.407	0.451
26	0.326	0.370	0.469	0.519
27	0.140	0.165	0.255	0.291
28	0.192	0.227	0.306	0.618
29	1.386	0.883	0.687	0.675
30	1.134	0.654	0.720	0.715
31	0.409	0.306	0.524	0.510
32	0.362	0.246	0.563	0.557
33	1.157	0.952	0.424	0.450
34	1.543	1.255	0.631	0.766
35	0.788	0.808	0.831	0.850
36	0.650	0.677	0.711	0.739

CRITERION	CR	CR + IR _{min}	CR + IR ₀
43/5N	13145.	13145.	13145.
43/0N	12937.	12937.	12937.

FILM 43 TARGET NUMBER 36

PREDICTOR NUMBER	PREDICTOR SET			
	2/6	1/6	2/2	1/2
1	746.000	755.000	750.000	775.000
2	827.000	822.000	851.000	873.000
3	677.000	678.000	810.000	788.000
4	741.000	768.000	755.000	776.000
5	157.000	160.000	144.000	138.000
6	250.000	371.000	93.000	93.000
7	259.000	261.000	316.000	298.000
8	167.000	171.000	164.000	156.000
9	3296.000	3378.000	3281.000	3363.000
10	222.000	209.000	292.000	274.000
11	1634.000	1388.000	1634.000	1388.000
12	389.000	429.000	429.000	429.000
13	0.069	0.066	0.076	0.074
14	1412.000	1253.000	1412.000	1253.000
15	2326.000	2221.000	2326.000	2221.000
16	13.000	11.000	15.000	11.000
17	4.000	1.000	5.000	1.000
18	3.000	3.000	3.000	2.000
19	16.000	14.000	18.000	13.000
20	168.000	170.000	169.000	167.000
21	9.000	4.000	13.000	5.000
22	10.000	8.000	9.000	7.000
23	178.000	178.000	177.000	174.000
24	0.607	0.564	0.607	0.564
25	0.092	0.102	0.080	0.017
26	0.181	0.175	0.048	0.097
27	0.048	0.053	0.038	0.008
28	0.100	0.212	0.025	0.051
29	1.189	0.838	1.179	0.791
30	0.976	0.689	0.920	0.590
31	0.373	0.295	0.371	0.283
32	0.328	0.256	0.315	0.228
33	1.650	1.631	2.194	2.159
34	1.036	0.704	3.398	3.204
35	0.933	0.938	0.911	0.919
36	0.374	0.883	0.837	0.849

CRITERION CR CR + IR_{min} CR + IR₀

43/5N	13037.	12420.	11704.
43/0N	13048.	12802.	12516.

FILM 43 TARGET NUMBER 40

PREDICTOR NUMBER	PREDICTOR SET			
	2/6	1/6	2/2	1/2
1	547.000	521.000	546.000	516.000
2	471.000	462.000	414.000	409.000
3	688.000	681.000	439.000	437.000
4	554.000	528.000	540.000	512.000
5	139.000	112.000	142.000	109.000
6	156.000	148.000	97.000	91.000
7	280.000	188.000	91.000	102.000
8	151.000	120.000	143.000	110.000
9	2526.000	2415.000	2526.000	2394.000
10	157.000	130.000	104.000	89.000
11	1367.000	1146.000	773.000	765.000
12	312.000	321.000	328.000	342.000
13	0.047	0.040	0.049	0.042
14	760.000	613.000	760.000	602.000
15	1956.000	1494.000	1956.000	1411.000
16	25.000	18.000	29.000	18.000
17	0.000	0.000	0.000	0.000
18	0.000	0.000	0.000	0.000
19	25.000	18.000	29.000	18.000
20	258.000	187.000	262.000	196.000
21	2.000	3.000	2.000	3.000
22	6.000	3.000	7.000	5.000
23	264.000	190.000	269.000	201.000
24	0.389	0.410	0.389	0.427
25	0.258	0.307	0.196	0.153
26	0.461	0.474	0.060	0.068
27	0.114	0.115	0.109	0.083
28	0.187	0.192	0.029	0.033
29	1.499	1.200	0.416	0.483
30	1.902	1.481	0.867	0.870
31	0.428	0.375	0.172	0.194
32	0.487	0.425	0.302	0.303
33	2.014	1.679	0.641	0.936
34	1.795	1.270	0.938	1.121
35	0.938	0.946	0.959	0.963
36	0.883	0.898	0.921	0.928
CRITERION	CR	CR + IR _{min}	CR + IR ₀	
43/5N	12838.	12838.	12838.	
43/0N	12750.	12750.	12750.	

FILM 43 TARGET NUMBER 46

PREDICTOR NUMBER	PREDICTOR SET			
	2/6	1/6	2/2	1/2
1	742.000	735.000	771.000	779.000
2	738.000	729.000	862.000	811.000
3	831.000	912.000	927.000	900.000
4	744.000	740.000	772.000	782.000
5	248.000	308.000	146.000	131.000
6	150.000	120.000	104.000	91.000
7	208.000	183.000	173.000	169.000
8	247.000	307.000	147.000	133.000
9	3566.000	3433.000	3703.000	3645.000
10	99.000	120.000	91.000	102.000
11	1442.000	1442.000	1306.000	1202.000
12	257.000	443.000	469.000	550.000
13	0.024	0.027	0.022	0.024
14	574.000	574.000	322.000	322.000
15	1107.000	1107.000	881.000	815.000
16	43.000	42.000	40.000	45.000
17	1.000	2.000	0.000	0.000
18	1.000	0.000	1.000	0.000
19	43.000	42.000	41.000	45.000
20	308.000	316.000	302.000	324.000
21	10.000	18.000	2.000	1.000
22	6.000	4.000	4.000	2.000
23	314.000	320.000	304.000	326.000
24	0.519	0.519	0.365	0.395
25	0.120	0.241	0.073	0.155
26	0.126	0.251	0.041	0.110
27	0.057	0.107	0.035	0.072
28	0.059	0.112	0.021	0.052
29	0.943	0.962	0.694	0.543
30	0.954	0.978	0.515	0.482
31	0.321	0.325	0.258	0.214
32	0.323	0.328	0.205	0.194
33	0.939	0.594	1.185	1.290
34	1.387	1.525	1.663	1.857
35	0.972	0.965	0.975	0.972
36	0.946	0.932	0.952	0.946

CRITERION	CR	CR + IR _{min}	CR + IR ₀
43/5N	11736.	11736.	11736.
43/0N	11585.	10520.	8659.

FILM 43 TARGET NUMBER 53

PREDICTOR NUMBER	PREDICTOR SET			
	2/6	1/6	2/2	1/2
1	703.000	611.000	687.000	609.000
2	766.000	664.000	796.000	673.000
3	584.000	498.000	646.000	543.000
4	695.000	604.000	683.000	605.000
5	200.000	144.000	196.000	148.000
6	174.000	106.000	174.000	99.000
7	187.000	130.000	207.000	137.000
8	201.000	146.000	197.000	148.000
9	3291.000	2922.000	3183.000	2892.000
10	208.000	165.000	258.000	197.000
11	1310.000	986.000	1310.000	946.000
12	320.000	320.000	351.000	359.000
13	0.071	0.065	0.079	0.064
14	1735.000	1503.000	1735.000	1503.000
15	2629.000	2128.000	2629.000	2128.000
16	52.000	65.000	45.000	47.000
17	0.000	1.000	0.000	0.000
18	3.000	3.000	6.000	5.000
19	55.000	68.000	50.000	53.000
20	408.000	461.000	418.000	435.000
21	6.000	6.000	8.000	9.000
22	15.000	10.000	25.000	13.000
23	423.000	470.000	443.000	448.000
24	0.660	0.706	0.660	0.706
25	0.169	0.171	0.060	0.109
26	0.238	0.250	0.188	0.193
27	0.092	0.102	0.031	0.028
28	0.135	0.143	0.104	0.107
29	0.836	0.614	0.907	0.553
30	0.710	0.485	0.646	0.406
31	0.302	0.235	0.312	0.217
32	0.262	0.195	0.244	0.169
33	0.935	0.903	1.056	0.926
34	1.075	1.226	1.190	1.384
35	0.937	0.944	0.919	0.932
36	0.881	0.893	0.850	0.872

CRITERION	CR	CR + IR _{min}	CR + IR ₀
43/5N	12148.	12148.	12148.
43/0N	12407.	12407.	12407.

FILM 43 TARGET NUMBER 61

PREDICTOR NUMBER	PREDICTOR SET			
	2/6	1/6	2/2	1/2
1	637.000	721.000	627.000	715.000
2	650.000	947.000	801.000	973.000
3	821.000	978.000	852.000	1030.000
4	646.000	733.000	637.000	730.000
5	184.000	197.000	190.000	203.000
6	199.000	111.000	171.000	96.000
7	241.000	175.000	233.000	155.000
8	192.000	204.000	199.000	212.000
9	2983.000	3394.000	2944.000	3380.000
10	201.000	233.000	201.000	242.000
11	1482.000	1482.000	1482.000	1482.000
12	237.000	580.000	395.000	856.000
13	0.050	0.048	0.048	0.047
14	1152.000	1152.000	1150.000	1057.000
15	1362.000	1362.000	1290.000	1290.000
16	35.000	40.000	45.000	64.000
17	2.000	0.000	0.000	0.000
18	2.000	1.000	1.000	0.000
19	36.000	41.000	46.000	64.000
20	291.000	346.000	291.000	365.000
21	4.000	2.000	3.000	3.000
22	9.000	9.000	7.000	7.000
23	300.000	354.000	297.000	372.000
24	0.846	0.846	0.891	0.819
25	0.289	0.356	0.359	0.441
26	0.263	0.033	0.064	0.059
27	0.126	0.151	0.152	0.181
28	0.116	0.016	0.031	0.028
29	1.327	1.055	1.364	1.073
30	1.280	0.565	0.850	0.523
31	0.399	0.345	0.405	0.349
32	0.390	0.220	0.298	0.207
33	1.310	0.888	1.226	0.764
34	1.211	1.577	1.363	1.615
35	0.933	0.931	0.932	0.928
36	0.874	0.872	0.872	0.866

CRITERION	CR	CR + IR _{min}	CR + IR ₀
43/5N	12577.	12577.	12577.
43/ON	11783.	11369.	10223.

FILM 76 TARGET NUMBER 9

PREDICTOR NUMBER	PREDICTOR SET			
	2/6	1/6	2/2	1/2
1	540.000	569.000	543.000	567.000
2	743.000	753.000	605.000	468.000
3	631.000	681.000	467.000	507.000
4	542.000	572.000	541.000	566.000
5	168.000	178.000	165.000	175.000
6	255.000	266.000	212.000	242.000
7	318.000	340.000	307.000	355.000
8	174.000	185.000	171.000	181.000
9	1921.000	2072.000	1946.000	2068.000
10	60.000	59.000	30.000	44.000
11	1706.000	1706.000	1706.000	1706.000
12	158.000	165.000	158.000	165.000
13	0.026	0.038	0.022	0.026
14	457.000	328.000	457.000	328.000
15	617.000	459.000	617.000	459.000
16	66.000	69.000	64.000	72.000
17	0.000	0.000	0.000	0.000
18	1.000	1.000	0.000	1.000
19	67.000	70.000	64.000	73.000
20	531.000	521.000	545.000	530.000
21	3.000	2.000	1.000	1.000
22	5.000	6.000	3.000	5.000
23	536.000	527.000	548.000	535.000
24	0.740	0.715	0.740	0.715
25	0.168	0.197	0.139	0.106
26	0.150	0.096	0.228	0.077
27	0.077	0.090	0.075	0.056
28	0.081	0.050	0.128	0.040
29	2.159	1.998	2.141	2.009
30	1.296	1.266	1.819	2.645
31	0.519	0.500	0.517	0.501
32	0.393	0.388	0.467	0.569
33	1.829	1.910	1.860	2.029
34	1.247	1.278	1.448	1.467
35	0.968	0.972	0.984	0.979
36	0.939	0.945	0.969	0.958

CRITERION	CR	CR + IR _{min}	CR + IR ₀
76/5N	24116.	22235.	16464.
76/CN	22111.	19812.	13509.
76/SW	26302.	25130.	23379.
77/5N	23588.	18988.	8887.

FILM 76 TARGET NUMBER 13

PREDICTOR NUMBER	2/6	PREDICTOR SET 1/6	2/2	1/2
1	468.000	468.000	469.000	469.000
2	469.000	469.000	396.000	396.000
3	400.000	400.000	425.000	425.000
4	467.000	467.000	468.000	468.000
5	98.000	98.000	98.000	98.000
6	117.000	117.000	77.000	77.000
7	76.000	76.000	71.000	71.000
8	98.000	98.000	97.000	97.000
9	1708.000	1708.000	1710.000	1710.000
10	33.000	33.000	33.000	33.000
11	559.000	559.000	559.000	559.000
12	210.000	210.000	225.000	225.000
13	0.022	0.022	0.018	0.018
14	237.000	237.000	237.000	237.000
15	538.000	538.000	538.000	538.000
16	66.000	66.000	63.000	63.000
17	0.000	0.000	0.000	0.000
18	1.000	1.000	2.000	2.000
19	67.000	67.000	65.000	65.000
20	530.000	530.000	531.000	531.000
21	0.000	0.000	0.000	0.000
22	5.000	5.000	5.000	5.000
23	535.000	535.000	536.000	536.000
24	0.440	0.440	0.440	0.440
25	0.145	0.145	0.093	0.093
26	0.147	0.147	0.141	0.141
27	0.078	0.078	0.049	0.049
28	0.079	0.079	0.068	0.068
29	0.194	0.194	0.191	0.191
30	0.191	0.191	0.411	0.411
31	0.088	0.088	0.087	0.087
32	0.087	0.087	0.170	0.170
33	0.775	0.775	0.724	0.724
34	0.649	0.649	0.922	0.922
35	0.980	0.980	0.980	0.980
36	0.962	0.962	0.962	0.962

CRITERION	CR	CR + IR _{min}	CR + IR ₀
76/5N	33590.	24837.	17606.
76/0N	34782.	30610.	27459.
76/SW	32590.	27097.	17606.
77/5N	20385.	16307.	3771.

FILM 76 TARGET NUMBER 17

PREDICTOR NUMBER	2/6	PREDICTOR SET 1/6	2/2	1/2
1	597.000	566.000	599.000	570.000
2	718.000	689.000	702.000	675.000
3	729.000	631.000	696.000	579.000
4	600.000	567.000	601.000	571.000
5	166.000	119.000	167.000	121.000
6	109.000	69.000	119.000	87.000
7	176.000	158.000	191.000	176.000
8	167.000	120.000	168.000	122.000
9	2193.000	2106.000	2198.000	2114.000
10	58.000	33.000	35.000	36.000
11	1023.000	987.000	1023.000	987.000
12	325.000	325.000	325.000	325.000
13	0.021	0.015	0.020	0.016
14	422.000	301.000	422.000	301.000
15	481.000	314.000	481.000	314.000
16	92.000	71.000	99.000	72.000
17	0.000	0.000	1.000	1.000
18	2.000	1.000	3.000	2.000
19	94.000	72.000	102.000	74.000
20	564.000	534.000	561.000	523.000
21	5.000	5.000	6.000	7.000
22	8.000	2.000	7.000	2.000
23	572.000	536.000	567.000	525.000
24	0.877	1.043	0.877	1.043
25	0.221	0.114	0.162	0.015
26	0.015	0.084	0.009	0.142
27	0.100	0.054	0.075	0.007
28	0.008	0.043	0.004	0.076
29	0.714	0.743	0.708	0.731
30	0.425	0.432	0.457	0.462
31	0.263	0.271	0.261	0.267
32	0.175	0.177	0.186	0.188
33	1.060	1.327	1.144	1.454
34	1.615	2.289	1.605	2.022
35	0.974	0.984	0.984	0.982
36	0.948	0.969	0.969	0.966

CRITERION	CR	CR + IR _{min}	CR + IR ₀
76/5N	24408.	19051.	10228.
76/CN	21517.	19644.	14917.
76/SW	26001.	24294.	21668.
77/5N	26880.	19130.	8204.

FILM 76 TARGET NUMBER 21

PREDICTOR NUMBER	2/6	PREDICTOR SET 1/6	2/2	1/2
1	421.000	422.000	426.000	425.000
2	546.000	563.000	561.000	572.000
3	840.000	800.000	895.000	931.000
4	433.000	432.000	440.000	438.000
5	106.000	101.000	107.000	105.000
6	108.000	130.000	115.000	137.000
7	331.000	296.000	264.000	255.000
8	139.000	125.000	140.000	137.000
9	1575.000	1552.000	1581.000	1548.000
10	96.000	77.000	105.000	89.000
11	1521.000	1509.000	1521.000	1509.000
12	349.000	355.000	418.000	454.000
13	0.058	0.047	0.031	0.054
14	626.000	494.000	626.000	494.000
15	758.000	459.000	758.000	459.000
16	45.000	50.000	43.000	50.000
17	0.000	1.000	0.000	0.000
18	1.000	1.000	0.000	0.000
19	46.000	51.000	43.000	50.000
20	520.000	519.000	520.000	519.000
21	5.000	5.000	3.000	2.000
22	5.000	5.000	4.000	4.000
23	525.000	524.000	524.000	523.000
24	0.826	1.076	0.826	1.076
25	0.995	0.896	1.101	1.191
26	0.538	0.421	0.595	0.628
27	0.332	0.309	0.355	0.373
28	0.212	0.174	0.229	0.239
29	2.613	2.576	2.570	2.551
30	1.786	1.680	1.711	1.638
31	0.566	0.563	0.562	0.560
32	0.472	0.457	0.461	0.450
33	3.123	2.931	2.467	2.429
34	3.065	2.227	2.296	1.861
35	0.939	0.950	0.934	0.943
36	0.885	0.905	0.875	0.891

CRITERION	CR	CR + IR _{min}	CR + IR ₀
76/5N	29487.	28451.	27824.
76/UN	33020.	33020.	33020.
76/SW	31218.	30359.	29484.
77/5N	27038.	25339.	23063.

FILM 76 TARGET NUMBER 22

PREDICTOR NUMBER	PREDICTOR SET			
	2/6	1/6	2/2	1/2
1	469.000	465.000	471.000	470.000
2	705.000	745.000	734.000	776.000
3	827.000	818.000	794.000	739.000
4	475.000	470.000	478.000	474.000
5	228.000	233.000	236.000	247.000
6	172.000	211.000	226.000	281.000
7	211.000	227.000	214.000	210.000
8	232.000	237.000	240.000	248.000
9	1742.000	1737.000	1760.000	1761.000
10	53.000	46.000	57.000	47.000
11	1662.000	1662.000	1662.000	1662.000
12	477.000	477.000	477.000	477.000
13	0.016	0.015	0.019	0.017
14	400.000	381.000	400.000	381.000
15	402.000	254.000	402.000	254.000
16	32.000	31.000	31.000	31.000
17	0.000	0.000	1.000	1.000
18	0.000	0.000	0.000	0.000
19	32.000	31.000	31.000	31.000
20	542.000	529.000	538.000	516.000
21	5.000	4.000	4.000	4.000
22	6.000	3.000	3.000	3.000
23	548.000	532.000	541.000	519.000
24	0.995	1.500	0.995	1.500
25	0.763	0.759	0.686	0.572
26	0.173	0.098	0.082	0.052
27	0.276	0.275	0.255	0.222
28	0.080	0.047	0.039	0.026
29	2.544	2.574	2.529	2.536
30	1.357	1.231	1.264	1.142
31	0.560	0.563	0.558	0.559
32	0.404	0.381	0.387	0.363
33	0.925	0.974	0.907	0.850
34	1.227	1.076	0.947	0.747
35	0.970	0.974	0.968	0.973
36	0.941	0.948	0.937	0.948

CRITERION	CR	CR + IR _{min}	CR + IR ₀
76/5N	25664.	24299.	21467.
76/0N	27947.	27947.	27947.
76/SW	29089.	29089.	29089.
77/5N	22043.	18324.	8414.

FILM 76 TARGET NUMBER 26

PREDICTOR NUMBER	PREDICTOR SET			
	2/6	1/6	2/2	1/2
1	580.000	575.000	579.000	564.000
2	594.000	615.000	594.000	625.000
3	1086.000	1135.000	1152.000	1160.000
4	661.000	653.000	712.000	680.000
5	197.000	207.000	193.000	202.000
6	134.000	110.000	110.000	93.000
7	416.000	369.000	417.000	381.000
8	308.000	306.000	357.000	342.000
9	1884.000	1904.000	1712.000	1738.000
10	671.000	608.000	1032.000	864.000
11	1973.000	2042.000	1973.000	1973.000
12	161.000	161.000	424.000	425.000
13	0.160	0.139	0.232	0.195
14	6979.000	4833.000	6979.000	4833.000
15	3479.000	2622.000	3479.000	2622.000
16	72.000	72.000	62.000	67.000
17	8.000	8.000	10.000	13.000
18	6.000	6.000	17.000	11.000
19	78.000	78.000	79.000	78.000
20	445.000	445.000	418.000	406.000
21	34.000	34.000	51.000	45.000
22	69.000	69.000	134.000	96.000
23	514.000	514.000	552.000	502.000
24	2.006	1.843	2.006	1.843
25	0.872	0.974	1.000	1.507
26	0.828	0.846	0.939	0.856
27	0.304	0.327	0.334	0.346
28	0.293	0.297	0.320	0.300
29	2.408	2.551	2.408	2.498
30	2.322	2.320	2.322	2.157
31	0.546	0.561	0.546	0.555
32	0.537	0.537	0.537	0.519
33	2.112	1.783	2.161	1.886
34	3.104	3.355	3.791	4.097
35	0.644	0.681	0.397	0.503
36	0.475	0.516	0.248	0.336

CRITERION	CR	CR + IR _{min}	CR + IR ₀
76/5N	38046.	38046.	38046.
76/0N	38788.	38788.	28788.
76/SW	37485.	37485.	37485.
77/5N	34685.	34685.	34685.

FILM 76 TARGET NUMBER 32

PREDICTOR NUMBER	2/6	PREDICTOR SET 1/6	2/2	1/2
1	611.000	644.000	605.000	642.000
2	678.000	711.000	677.000	704.000
3	539.000	580.000	486.000	542.000
4	603.000	638.000	593.000	633.000
5	155.000	155.000	155.000	148.000
6	122.000	132.000	120.000	125.000
7	170.000	178.000	93.000	88.000
8	159.000	158.000	154.000	146.000
9	2052.000	2191.000	2037.000	2174.000
10	207.000	201.000	185.000	185.000
11	1421.000	1421.000	1023.000	1023.000
12	140.000	140.000	174.000	301.000
13	0.103	0.092	0.102	0.092
14	1450.000	1091.000	1450.000	1091.000
15	2765.000	2331.000	2765.000	2331.000
16	65.000	72.000	96.000	87.000
17	2.000	2.000	3.000	4.000
18	4.000	5.000	3.000	3.000
19	69.000	76.000	72.000	90.000
20	541.000	551.000	543.000	555.000
21	20.000	16.000	22.000	20.000
22	40.000	40.000	44.000	47.000
23	581.000	591.000	587.000	602.000
24	0.524	0.468	0.524	0.468
25	0.118	0.099	0.197	0.156
26	0.205	0.184	0.282	0.230
27	0.063	0.052	0.109	0.084
28	0.114	0.101	0.164	0.229
29	1.326	1.207	0.691	0.593
30	1.096	0.999	0.511	0.452
31	0.399	0.376	0.257	0.229
32	0.354	0.333	0.204	0.185
33	1.097	1.148	0.600	0.595
34	1.393	1.348	0.775	0.704
35	0.899	0.908	0.909	0.915
36	0.817	0.832	0.833	0.843

CRITERION	CR	CR + IR _{min}	CR + IR ₀
76/5N	28909.	28777.	28464.
76/UN	28365.	28365.	28365.
76/SW	28316.	28316.	28316.
77/5N	24192.	22925.	20299.

FILM 76 TARGET NUMBER 36

PREDICTOR NUMBER	PREDICTOR SET			
	2/6	1/6	2/2	1/2
1	501.000	494.000	492.000	493.000
2	578.000	601.000	565.000	602.000
3	527.000	5417.000	602.000	593.000
4	502.000	495.000	496.000	496.000
5	130.000	125.000	129.000	126.000
6	100.000	101.000	108.000	112.000
7	158.000	146.000	203.000	200.000
8	131.000	126.000	134.000	130.000
9	1813.000	1778.000	1773.000	1761.000
10	60.000	59.000	73.000	42.000
11	1365.000	1085.000	1365.000	1085.000
12	309.000	309.000	309.000	309.000
13	0.031	0.031	0.033	0.032
14	480.000	389.000	480.000	389.000
15	806.000	806.000	806.000	806.000
16	45.000	47.000	44.000	49.000
17	1.000	1.000	2.000	2.000
18	2.000	2.000	2.000	2.000
19	47.000	49.000	46.000	51.000
20	457.000	453.000	452.000	451.000
21	5.000	5.000	4.000	5.000
22	6.000	6.000	5.000	8.000
23	463.000	459.000	457.000	459.000
24	0.596	0.483	0.596	0.483
25	0.052	0.047	0.224	0.203
26	0.088	0.140	0.065	0.015
27	0.025	0.023	0.101	0.092
28	0.046	0.075	0.032	0.008
29	1.725	1.196	1.774	1.201
30	1.362	0.805	1.416	0.802
31	0.463	0.374	0.470	0.375
32	0.405	0.287	0.415	0.286
33	1.215	1.168	1.574	1.587
34	1.580	1.446	1.880	1.786
35	0.967	0.967	0.959	0.976
36	0.936	0.936	0.921	0.953

CRITERION	CR	CR + IR _{min}	CR + IR ₀
76/5N	23557.	22589.	19605.
76/0N	28718.	28718.	28718.
76/SW	28352.	28352.	28352.
77/5N	20780.	18522.	10818.

FILM 76 TARGET NUMBER 40

PREDICTOR NUMBER	PREDICTOR SET			
	2/6	1/6	2/2	1/2
1	362.000	387.000	361.000	390.000
2	250.000	257.000	255.000	262.000
3	368.000	427.000	369.000	435.000
4	362.000	388.000	362.000	391.000
5	107.000	113.000	107.000	114.000
6	87.000	92.000	78.000	75.000
7	229.000	322.000	113.000	134.000
8	112.000	122.000	107.000	114.000
9	1334.000	1421.000	1326.000	1422.000
10	38.000	37.000	41.000	39.000
11	916.000	916.000	916.000	916.000
12	188.000	199.000	188.000	221.000
13	0.027	0.024	0.029	0.024
14	315.000	241.000	315.000	241.000
15	1001.000	645.000	1001.000	645.000
16	60.000	58.000	61.000	59.000
17	0.000	0.000	0.000	0.000
18	2.000	1.000	1.000	1.000
19	62.000	59.000	62.000	60.000
20	420.000	439.000	421.000	438.000
21	3.000	3.000	3.000	2.000
22	7.000	6.000	5.000	3.000
23	427.000	445.000	426.000	441.000
24	0.351	0.374	0.351	0.374
25	0.017	0.103	0.022	0.115
26	0.472	0.661	0.447	0.660
27	0.008	0.049	0.011	0.055
28	0.191	0.249	0.183	0.248
29	1.530	1.367	1.537	1.349
30	2.664	2.564	2.592	2.496
31	0.433	0.406	0.435	0.403
32	0.571	0.562	0.564	0.555
33	2.140	2.850	1.056	1.175
34	2.632	3.500	1.449	1.787
35	0.972	0.974	0.969	0.973
36	0.942	0.949	0.940	0.947

CRITERION	CR	CR + IR _{min}	CR + IR ₀
76/5N	24822.	23727.	20281.
76/0N	30323.	30323.	30323.
76/SW	26757.	25537.	23786.
77/5N	24739.	21431.	16354.